The Effects of Cryptocurrency Wealth on Household Consumption and Investment*

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Abstract

This paper uses transaction-level data across millions of accounts to identify cryptocurrency investors and evaluate how fluctuations in individual crypto wealth affect household consumption, equity investment, and local real estate markets. We estimate an MPC out of unrealized crypto gains that is more than double the MPC out of unrealized equity gains but smaller than the MPC from exogenous cash flow shocks. This MPC is mostly driven by increases in cash/check spending and mortgages. Moreover, households sell crypto to increase both discretionary as well as housing spending. As a result, crypto wealth causes house price appreciation—counties with higher crypto wealth see higher growth in home values following high crypto returns. Our results indicate that cryptocurrencies have substantial spillover effects on the real economy through consumption and investment into other asset classes.

Keywords: cryptocurrency, Bitcoin, Ethereum, 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, there is uncertainty regarding potential spillovers to the broader economy—spillovers that could have implications for policymakers and matter for household welfare. While some attention has focused on crypto and financial stability, lack of data due to the anonymous nature of blockchain transactions 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 from millions of U.S. households' bank accounts and credit card payments to analyze how crypto wealth influences the broader 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 prices in local real estate markets. We identify crypto users based on transfers into and out of major cryptocurrency exchanges and impute crypto wealth based on the timing of the 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, 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, consistent with some survey evidence (Benetton and Compiani, 2022), and are more likely to deposit money in traditional equity brokerages than non-adopters. Consistent with these income differences, crypto adopters spend a higher fraction of their income on discretionary categories like entertainment and restaurants.

On average, households appear to treat crypto as one piece of a larger investment portfolio. Crypto users tend to be active traders in equity markets, often simultaneously investing in both crypto assets and traditional equity securities. We find some evidence suggesting that households re-balance their portfolios by selling crypto after large gains and depositing money into traditional brokerages. Despite this evidence of financial sophistication, we also find that some crypto users chase crypto gains, and overall adoption appears to be driven in large part by the salience of high returns. The highest quantity of monthly new crypto users during our sample was added in 2017 when Bitcoin experienced one of its highest ever 12-month returns.

We then examine consumption responses to household-level crypto gains. Using a monthly panel of users, we look at how spending patterns change following changes in crypto wealth. On average, we estimate a marginal propensity to consume (MPC) out of crypto wealth of $0.08. 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 quantitatively 2–3 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 Kaplan and Violante (2014); Johnson, Parker, and Souleles (2006)). This suggests that households treat crypto gains like a hybrid of an exogenous cash flow shock and a traditional portfolio investment. Despite the lottery-like returns of crypto over this time period, the estimated MPC is much smaller than those found in studies of lottery winnings, which range from 50% to nearly 100% (Fagereng, Holm, and Natvik, 2021). Overall, the aggregate effect of these increases in crypto wealth for the households in our sample indicates an approximate $20 billion increase in consumption. If the consumption out of non-retail crypto gains is similar to our estimates, the total U.S. effect is likely between $80–$100 billion.

The near-term MPC out of crypto wealth is larger for higher income households, and the largest identifiable change in spending comes from higher mortgage expenses. These individual-level changes in housing consumption suggest that crypto returns could potentially spill over into the local real economy—increased demand for homes could create local housing price pressure. 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 house prices might cause households to withdraw crypto investments in order to afford a house purchase. Additionally, counties that become wealthier, perhaps due to changes in education, occupation, or industry concentration, are likely to simultaneously invest more in all assets. In the last part of the paper, 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 and fix crypto wealth in the pre-period, noting an absence of differential trends in the period preceding the run-up in prices. We further show that high crypto wealth counties experience a sharp increase in crypto withdrawals following the Bitcoin price shock, but experience no discontinuous change in traditional brokerage withdrawals. We find significantly higher house price appreciation for counties that had high pre-2017 crypto wealth in the months following the price run-up. House prices in high crypto wealth counties grow about 46 basis points faster than house prices in low crypto wealth counties, explaining roughly 12% of the standard deviation in house price growth during this time period.

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 the 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. Using passive crypto portfolio gains as an instrument for changes in county-level crypto wealth, we find that 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 $0.23 over the following six months.

Because this instrument is based on historical crypto portfolios, it alleviates concerns about reverse causality. However, to identify the effect of crypto wealth on local house prices, this instrument must satisfy the exclusion restriction that passive gains in crypto wealth are uncorrelated with any other change in non-crypto wealth that might affect house prices. 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. The most plausible exception is equity market returns. Counties with high crypto wealth also tend to have high equity market participation and crypto returns are positively correlated with equity market returns, at least in some periods. However, our 2SLS results are robust to modifying the instrument to use crypto returns in excess of market equity returns.

Unlike papers which describe characteristics of cryptocurrency investors or crypto trading behavior (e.g., Benetton and Compiani, 2022; Chava, Hu, and Paradkar, 2022; Divakaruni, Zimmerman, et al., 2021; Hackethal, Hanspal, Lammer, and Rink, 2022; Makarov and Schoar, 2021), we examine the interaction of cryptocurrency price fluctuations with household consumption and investment behavior. In contrast to prior papers, our data allow us to link a broad set of U.S. retail crypto traders to a relatively complete set of other financial transactions. Most similar to our study is Kogan, Makarov, Niessner, and Schoar (2022) which uses transaction-level data to characterize the investment decisions of retail crypto users. Unlike our study, Kogan et al. (2022) observe actual crypto and equity trades but do not directly observe any other income or consumption transactions, limiting the ability to make inferences about effects on the real economy.

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 marginal propensity to consume (MPC) out of capital gains is on the order of 0.02-0.04 and is significantly lower than out of dividends. Case, Quigley, and Shiller (2005), Aladangady (2017), Berger, Guerrieri, Lorenzoni, and Vavra (2018), and Chen, Michaux, and Roussanov (2020) look at 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).

We examine household consumption decisions after realizing gains from crypto—a new asset class with extreme volatility. 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 (2018), and Griffin, Kruger, and Mahajan (2023) who leverage 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 2022. 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, the data provider does provide a monthly panel estimating the current residence (city) of the user. For a large fraction of users, we are also able to impute the zip code of their residence based on the physical location of merchants that frequently appear in transactions.[1]

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 (2021) utilize the same data provider as in this paper to study the rollout of peer-to-peer financial transfer technology and how it impacts savings and consumption across U.S. households, and Di Maggio, Williams, and Katz (2022) use these same 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

[1]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.

from a highly selected sample of the 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 2014 to 2022 are very similar across our data and the Census Retail Sales survey. On average, the correlation in monthly spending from these two sources is approximately 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.[2] While this is unlikely to be strictly true for users in the data, 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

[2] 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.

sub-sample of 95,965 users drawn randomly from the top 10% of the sample based on this quality 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 a major exchanges (eg. ‘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, since 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 suggests that we are likely to capture the majority of deposits and withdrawals from retail crypto exchanges.

While users interact with exchanges using bank transfers, debit cards, and credit cards, the vast majority of transactions are through a checking account or debit card, 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 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.[3] Gemini makes up another 5% of dollar flows, while the remaining

[3]Coinbase launched in 2012 and is now the single largest U.S. crypto exchange. As of December 2021, the total value of crypto assets held on Coinbase represented about 11.5% of total global crypto assets.

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 the household's asset mix on the prior day.[4] 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 total market capitalization of the coins on that day.[5] 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.

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

[5]Results are robust to basing weights on transaction volume instead of market capitalization or broadening the basket of cryptocurrencies we use to weight holdings.

The summary statistics for household crypto wealth are reported in Panel A of Table 1. On average, crypto users in our sample have a crypto portfolio worth about $6,000. However, this average is skewed due to a small percentage of users with very large portfolios. The median crypto portfolio is only $336, and the 75th percentile is $1,800. In contrast, the maximum portfolio is worth about $9 million by 2022.

The skew in crypto portfolio wealth broadly matches the skew in U.S. household equity holdings. In Appendix Figure A.5, 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 80th–99th 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 2022. This is very similar to the estimated share of the U.S. population that has traded crypto based on recent survey data.[6]

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

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

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 in excess of $1 trillion. 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. (2022), Chava, Hu, and Paradkar (2022), Divakaruni, Zimmerman et al. (2021), 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 how the consumption patterns of household crypto investors compare to other households.

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 that are 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 $8,176 for crypto investors relative to $7,356 for non-investors. Perhaps unsurprisingly given the income differences, crypto adopters also actively invest substantially more in traditional brokerage accounts.[7]

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 nearly 1.2 percentage points more on restaurants than non-crypto investors. Crypto adopters also spend substantially more on cash/check purchases.

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 limited 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 scattered throughout the U.S. began to accumulate crypto wealth of $1,000 per household or more. By the end of 2021, however, 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

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

have differential effects on the local economy across counties, which we investigate in Section 5.

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.[8] To the extent that the views expressed in these surveys are representative, crypto users are likely to double down on their crypto investments rather than rebalance crypto gains into equity markets.

We evaluate the relationship 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 for individuals with total cryptocurrency deposits of $100,000 or less. 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 relationship flattens at the high end of crypto deposits. For instance, the average user who

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

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. Together, this evidence suggests that there are two types of retail crypto investors. For one type of investor, crypto makes up a small portion of an investment portfolio dominated by traditional brokerage deposits. In contrast, there exist a minority of crypto investors who invest very heavily in crypto and comparatively little in traditional brokerages.

To explore this relation in more depth, we examine household investment decisions following crypto gains (and losses). For each household, 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 is about \$390 with a standard deviation of \$3,200. About 43% of household-quarters experience a quarterly loss. Conditional on a positive gain, the average quarterly gain in crypto wealth is about \$1,060. Conditional on a loss, the average quarterly loss is about \$433.

We examine the relation between crypto gains and future investment decisions by estimating OLS regressions of the following form:

$$\text{Invest}_{i,q} = \beta\, \text{AvgCryptoGains}_{i,q} + \alpha_i + \delta_{s,q} + \Gamma\, X_{i,q-1} + \varepsilon_{i,q}. \qquad (3)$$

The dependent variable, $\text{Invest}_{i,q}$, represents the total dollars invested by household i over quarter q. We separately examine crypto investments and traditional brokerage investments. We include both household (α_i) and state by quarter ($\delta_{s,q}$) fixed effects and include controls for lagged income and prior investment deposits. 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 investment behavior. We winsorize crypto gains at the 1^{st} and 99^{th} percentiles to alleviate concerns over measurement error in crypto wealth, and trim income at the 1^{st} and 99^{th} percentiles to remove households for which our transaction data is unreliable. We cluster standard errors at the household level. The estimate of interest, β, represents the additional dollars invested in crypto exchanges or traditional brokerages during a quarter for each dollar of quarterly crypto gains received on average over the last year.

We report the results from estimating Equation 3 in Table 3. In column (1), we estimate the relation between crypto gains and future crypto deposits. We find that a larger gain in crypto wealth is associated with depositing more money to crypto exchanges—a \$1 increase in crypto wealth leads to an additional \$0.06 of crypto deposits over the quarter. This result suggests 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. (2022).

In column (2) of Table 3, we examine the relation between crypto wealth gains and future equity investment, proxied by deposits to traditional brokerages.[9] We find that households that experience larger gains in crypto wealth invest more in traditional brokerages. A \$1 increase in crypto wealth is associated with \$0.03 of additional traditional investment. This result suggests the possibility that some households rebalance crypto gains into traditional investments.

To shed more light on the possibility of portfolio re-balancing, we estimate the relation be-

[9]The brokerages included in this measure did not offer crypto trading during this time period.

tween crypto gains and future crypto withdrawals in column (3). We find a positive and significant relation between crypto gains and future crypto withdrawals; a $1 increase in crypto wealth is associated with $0.09 of future crypto withdrawals. Importantly, the estimates in columns (1) and (2) are driven by different households, which suggests that some households exhibit momentum in crypto investing and thus double down on unrealized crypto gains while other households realize their crypto gains in the form of withdrawals and rebalance their portfolio.[10]

4 Consumption out of Crypto Wealth

How do increases in crypto wealth affect household consumption? We first answer this question by re-estimating Equation 3 using total quarterly household consumption as the dependent variable. The 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 in Table 4. Using the full sample, we find a small, statistically insignificant MPC.

One potential confounding factor with this MPC estimate is that the last 2.5 years of our sample occur following the Covid pandemic. Overall spending falls during this period, consistent with limited opportunities for travel and other discretionary spending. This fall in spending is particularly pronounced for high-income households (e.g., Chetty, Friedman, Hendren, Stepner, et al., 2020), and crypto investing is also correlated with income. These features of the data are likely to bias downward estimated MPCs out of crypto wealth during the Covid period.

To address this concern, in column (2) we interact crypto gains with an indicator for quarters that occur during the Covid period. We find that crypto gains are strongly negatively associated with spending during the Covid period; during the pre-Covid period, however, the MPC out of

[10]In unreported results, we find that crypto gains positively predict the absolute value of net crypto withdrawals.

crypto wealth was about \$0.09 per dollar of crypto gains.[11] In column (3), we limit the sample to the pre-Covid period and find a similar MPC. This MPC out of crypto wealth is approximately 3 times larger than estimates of the MPC out of equity wealth, which for individuals at a similar point of the wealth distribution are about \$0.03 (Di Maggio, Kermani, and Majlesi, 2020). However, it is lower than estimates of the MPC out of lottery winnings of about \$0.50 (Fagereng, Holm, and Natvik, 2021). Consequently, it appears that households treat crypto gains as something more lottery-like than an equity gain, but more equity-like than actual lottery winnings.

One concern with this estimated MPC is that realized crypto gains might be endogenous to household spending. An investor that 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 $\text{BTCWealth}_{i,q-4}$

[11] As additional evidence that the negative MPC during Covid is driven by a fall in discretionary spending, we find that the MPC for mortgage spending is similar in both magnitude and significance in the full sample vs. the pre-Covid period.

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 crypto gains, we estimate the first stage as follows:

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

Unsurprisingly, passive gains strongly predict actual household crypto gains—the first stage F-statistic is about 2,500 in our main specification. We then use the predicted crypto gains from Equation 5 to estimate the following second stage regression:

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

For this 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 in Equation 6 in column (4) of Table 4. We find a positive and highly statistically significant MPC of about $0.08. This estimate is only slightly smaller than our OLS estimate. However, even this smaller MPC is still more than 2.5 times larger than conventional estimates of the MPC out of equity wealth. We next investigate whether households treat crypto losses differently from gains by interacting an indicator variable for quarters in which crypto gains are negative with crypto gains.[12] The results, reported in column (5), show that the estimated coefficient on the interaction with negative gains is statistically insignificant, though the combined effect suggests a much more muted MPC in response to crypto losses than to gains. One key takeaway is that while consumption may not be perfectly symmetric in gains and losses, we would still anticipate reductions in spending following crypto crashes.

Another dimension in which there might be heterogeneity in consumption responses is income. To explore this possibility, we split our sample of households into quartiles based on total income in the first year that the household appears in our sample. We then re-estimate our 2SLS specification separately for each sub-sample and report the results in Panel (A) of Table 5. There is no significant change in spending following crypto gains for lower income households. Recall that our measure of crypto gains represents mostly unrealized paper gains. Lower income households do not consume out of unrealized crypto gains.[13] In contrast, MPC estimates for households in the top two quartiles of income range from \$0.08 to \$0.10 and are significant at the 5% level.

In Panel (B) of Table 5, we examine asymmetries between crypto gains and losses separately for each income quartile. We find no evidence of asymmetries for households in the top three quartiles of income. However, the picture is different for the lowest-income households. For these households, the combined coefficients mean that low-income households actually *increase* consumption by 0.22 following \$1 of crypto losses. How, and why, do low-income households increase consumption following a loss? We find that households are much more likely to withdraw crypto following losses. While this is a loss relative to 12-month prior crypto portfolio balance, the households now have new dollars available in their checking account. For low-income house-

[12]To estimate this regression, we use both passive gains and passive gains multiplied by an indicator for quarters in which passive gains are negative as instruments. The F-statistic reported in Table 4 accounts for both instruments.

[13]In unreported results, we find no evidence that MPCs vary based on other proxies for liquidity constraints such as low account balances or overdrawn checking accounts.

holds, it appears that having this money converted from hard-to-spend cryptocurrency into liquid cash leads them to spend more.

Finally, we explore how different categories of consumption respond to changes in crypto wealth in Table 6. The largest effect is in spending by cash/check (see column (4)); this spending represents about 80% of the overall MPC. Most of the remaining consumption effect comes from increases in mortgage payments. Both of these results are consistent with purchasing a new home or other large durable purchases like automobiles, since many expenses associated with a house and auto purchase are made by check.[14] In the next section, we examine new house purchases in more depth.

The results in this section show that households change their investment and consumption behavior following increases in crypto wealth. While some households rebalance their investment portfolio by withdrawing crypto assets and depositing money to traditional brokerages, other households chase crypto gains by depositing even more money to crypto exchanges. The MPC out of crypto wealth is 2–3 times larger than the MPC out of equity wealth, but smaller than the MPC out of lottery gains.

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 household expenses and balance sheet liquidity. The trends visible in Figure 3 suggest that at least one additional

[14]Unfortunately, the data do not allow us to determine what cash/check expenses are for. Note that cash/check purchases make up about 18–21% of overall household spending on average (see Table 2).

driver of crypto withdrawals is crypto returns. At the aggregate level, withdrawals clearly spike following large Bitcoin returns. Aiello et al. (2023) examine this relation more formally and find evidence that lagged Bitcoin returns positively predict retail crypto withdrawals. This relation induces some variation in household withdrawal decisions.

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

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

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 withdrawals to be greater than \$5,000 in our baseline analysis. There are roughly 3,109 such events in our sample with a mean withdrawal size of about \$17,000. Included in these regressions are account fixed effects (α_i) and year fixed effects (γ_y); we also control for lagged monthly income. We restrict the analysis to a window that is 12 months before and after event τ_i.

The event study establishes a causal relationship in the timing between cryptocurrency withdrawals and consumption changes. It does not, however, establish that the withdrawal caused the change in spending. This is because the decision to withdraw could be done in expectation of changes in future consumption. 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. 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.

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.

Results in Table 7 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 $7,877 relative to that household's spending in the prior year. In contrast to consumption out of mostly unrealized crypto wealth gains, there are large increases in spending across most consumption categories. We see particularly large increases in spending by cash/check and spending on general merchandise. We also see large increases in discretionary spending on entertainment, travel, and restaurants. Finally, crypto withdrawals are also spent on housing expenses–mortgage spending increases by about $600, insurance increases by about $180, and utilities go up by roughly $140. In fact, while they are less directly tied to housing, even the increases in spending by check and on general merchandise could represent down payments, escrow deposits, and furnishing a new house.

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.[15] Mortgage spending is constant in the 6-months leading up to a large crypto withdrawal, but rises significantly thereafter. In contrast to mortgage spending, rent spending (bottom panel) is constant across the event window, suggesting that the increase in spending we observe is not driven by a change in the overall price of housing.

[15] A large withdrawal is defined as ≥$5,000. We include account and year fixed effects in this regression.

We next examine how the effect of crypto withdrawals on mortgage spending varies with the size of the withdrawal. Table 8 reports results for mortgage expenses estimated using the model from Equation 7, but increasing the large withdrawal threshold from $5,000 up to $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 $732 over the next year, about 20% more than the estimated 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 8, 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 4.7 percentage points, or about 43% relative to the sample mean.[16]

5 Aggregate Impact of Crypto Wealth on Local House Prices

In Section 4, we show that households spend more on housing following increases in crypto wealth. 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

[16]We also find that existing homeowners significantly increase their mortgage payments following large crypto withdrawals, suggesting that some existing owners upgrade to a more expensive house.

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 scale this measure by the number of households in our transaction 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, which allows us to compare across counties despite variation in housing market size.

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 national trends in housing prices. We further include the lagged monthly ZHVI to control for local housing market dynamics. Our standard errors are clustered at the county level, 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

To study the effect of the growth in crypto portfolio values on county house prices, 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 in Bitcoin prices make it an attractive setting to study the effect of increases in crypto wealth on local 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

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

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. We include the 18-month window surrounding this event and define $Post_t$ as an indicator equal to one for county-months beginning in May 2017. 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.

For this approach to identify the causal effect of changes in crypto wealth on house prices, we must assume that if Bitcoin prices had not skyrocketed, house price growth in high and low crypto wealth counties would have evolved similarly. To examine this parallel trends assumption, in Figure 8 we plot the coefficients obtained from estimating a version of Equation 11 that interacts the high crypto wealth indicator with indicators for each month in the 18-month window 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 the 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-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 Nasdaq returns in the months surrounding the crypto wealth shock (see Appendix Figure A.2).[18] While Bitcoin returns are 20-50x Nasdaq returns over this time period, Nasdaq returns are quite high for equities, ranging from 20 to 30 percent. Importantly, though, Nasdaq 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.3 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. Finally, our difference-in-differences results are also robust to controlling for county-level exposure to equity interacted with the post indicator.

We estimate the difference-in-differences specification in Equation 11 and report the results in Table 9. 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.

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

[18]We choose Nasdaq returns as our benchmark here to reflect our prior that cryptocurrency investors are more likely to tilt toward tech stocks.

[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 estimated effect of crypto wealth on county house prices in column (1) indicates that house prices grow about 46 basis points faster in the post-period in high crypto wealth counties relative to low crypto wealth counties, or roughly 12% of the standard deviation in house price growth over 2018. In dollar terms, the estimate in column (3) indicates that house prices are about $1,878 higher in high crypto wealth counties in the nine months following the Bitcoin price shock. This is about a one percent increase in prices relative to the mean county house price. The continuous specification implies a similar, but smaller economic magnitude. The estimated elasticity combined with a change in county crypto wealth from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile indicates that house prices increase by about 19 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 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 is the price of Bitcoin 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

[20] The 25$^{\text{th}}$ percentile is 1.2 and the 75$^{\text{th}}$ percentile is 3.2, so the elasticity implies an increase of $(\frac{3.2}{2.2})^{0.00189} - 1$.

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.[21]

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 (due to a combination of Bitcoin and Ethereum returns over the prior year and heterogeneity in lagged crypto wealth) must be uncorrelated with any other change in non-crypto wealth that might affect house prices, 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.

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. To alleviate this concern, we construct an alternative instrument that represents the excess Bitcoin return over equity market returns during the contemporaneous period.

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

Under this definition, our instrument represents the passive excess return of investors' Bitcoin and Ethereum portfolios relative to the return on Nasdaq (QQQ). This modification results in

[21]To alleviate any concerns that the 12-months prior portfolio is potentially endogenous with house prices, we replicate our results using portfolio values from 24-months prior. The results are robust to this change and reported in Appendix Table A.2.

estimates of the effect of additional crypto wealth in a county relative to how a similar allocation to large tech firms would have performed. Using $\text{ExcessPassiveGains}_{c,t}$ as the instrument yields similar results, suggesting that equity returns do not drive our results.

Using these exogenous crypto gains as an instrument, we estimate the first stage regression:

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

Unsurprisingly, the returns to initial crypto holdings strongly predict county-level crypto gains—the first stage F-statistic ranges from 3,000 to 6,000 across our main specifications. We then use the predicted crypto gains from Equation 14 to estimate the following second stage regression:

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

where we measure changes in the housing price index, $ZHVI_{c,t}$ over the three months following the current month. Table 10 reports the results from estimating the 2SLS specification in Equation 15.[22] We find that growth in county crypto wealth causes county house prices to go up over the next 3 months, and to rise even more over the following 6 months.[23] The estimates are highly statistically significant, robust to including fixed effects, and similar using either the *PassiveGains* or *ExcessPassiveGains* instruments.

Looking across Table 10, the estimates indicate that \$1 of crypto wealth gains per person in a county drive house prices up by about \$0.078 over the next three months, or about \$0.23 over the following six months. These estimates imply that a one standard deviation increase in county per capita crypto gains leads to a \$745 dollar increase in county house prices over the next six

[22]We report OLS, first stage, and reduced form results in Appendix Table A.1.

[23]Note that the house price growth plateaus after 6 months. The (unreported) estimated coefficient on 12-month house price changes is nearly identical to the estimate for 6-months.

months. This is about a 40 basis point increase in prices relative to the sample mean, 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.

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, some households chasing crypto gains and other households rebalancing a portion of crypto gains into traditional brokerage investments. Households also use crypto wealth to increase their discretionary consumption. The MPC out of crypto wealth is substantially higher than the MPC out of equity wealth, but lower than the MPC out of lottery winnings.

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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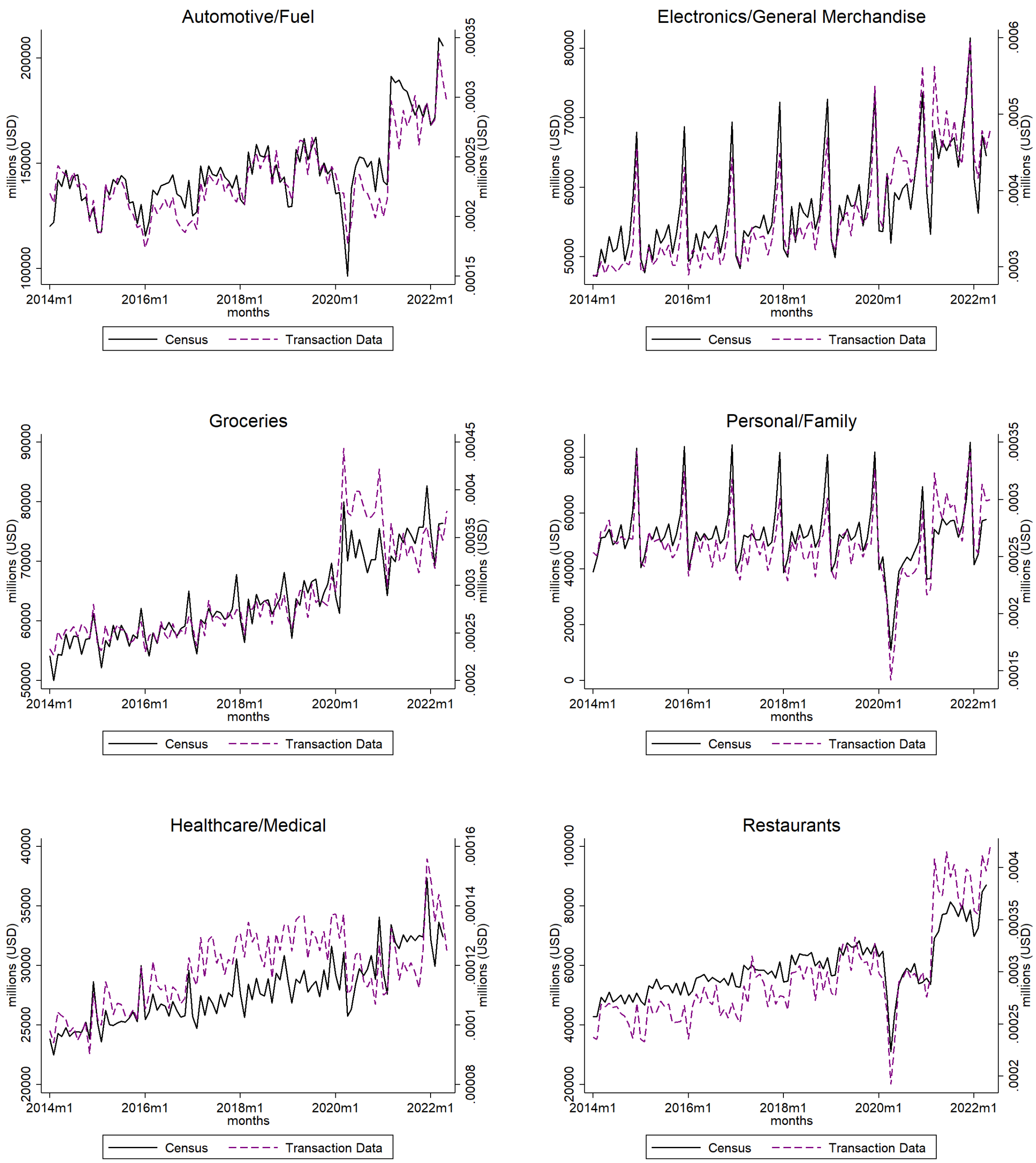


Figure 1. Spending in Data vs. Census Retail Sales. Each panel displays two monthly series from January 2014–July 2022. The solid line displays total sales in the specified category from the Census Retail Sales. The dotted line displays spending per user in the specified category as observed in the data from the large transaction aggregator.

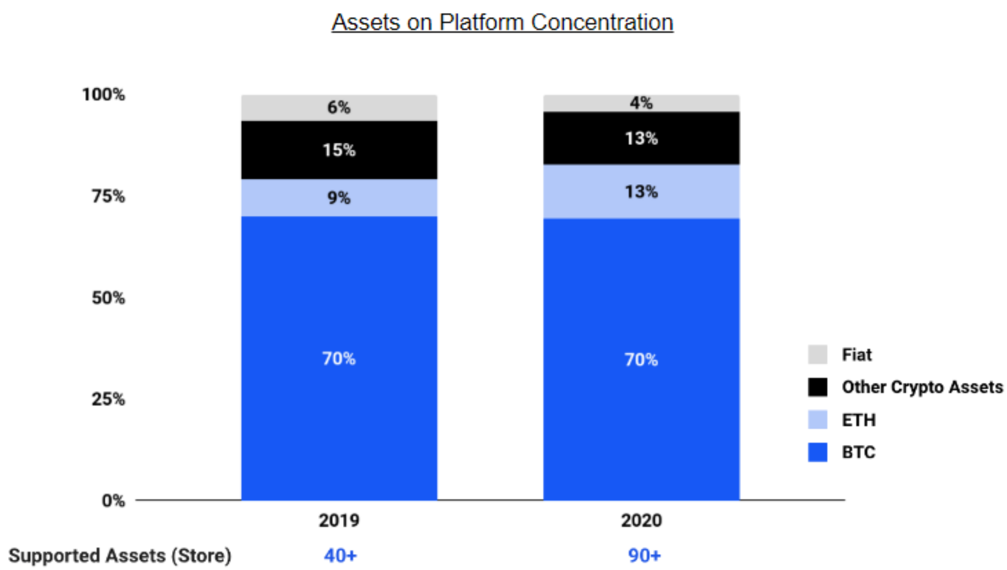


Figure 2. Cryptocurrency Assets Held Through Coinbase. This figure shows the percentage of various cryptocurrencies held on Coinbase in 2019 and 2020. Source: Coinbase S-1 filed on March 23, 2021.

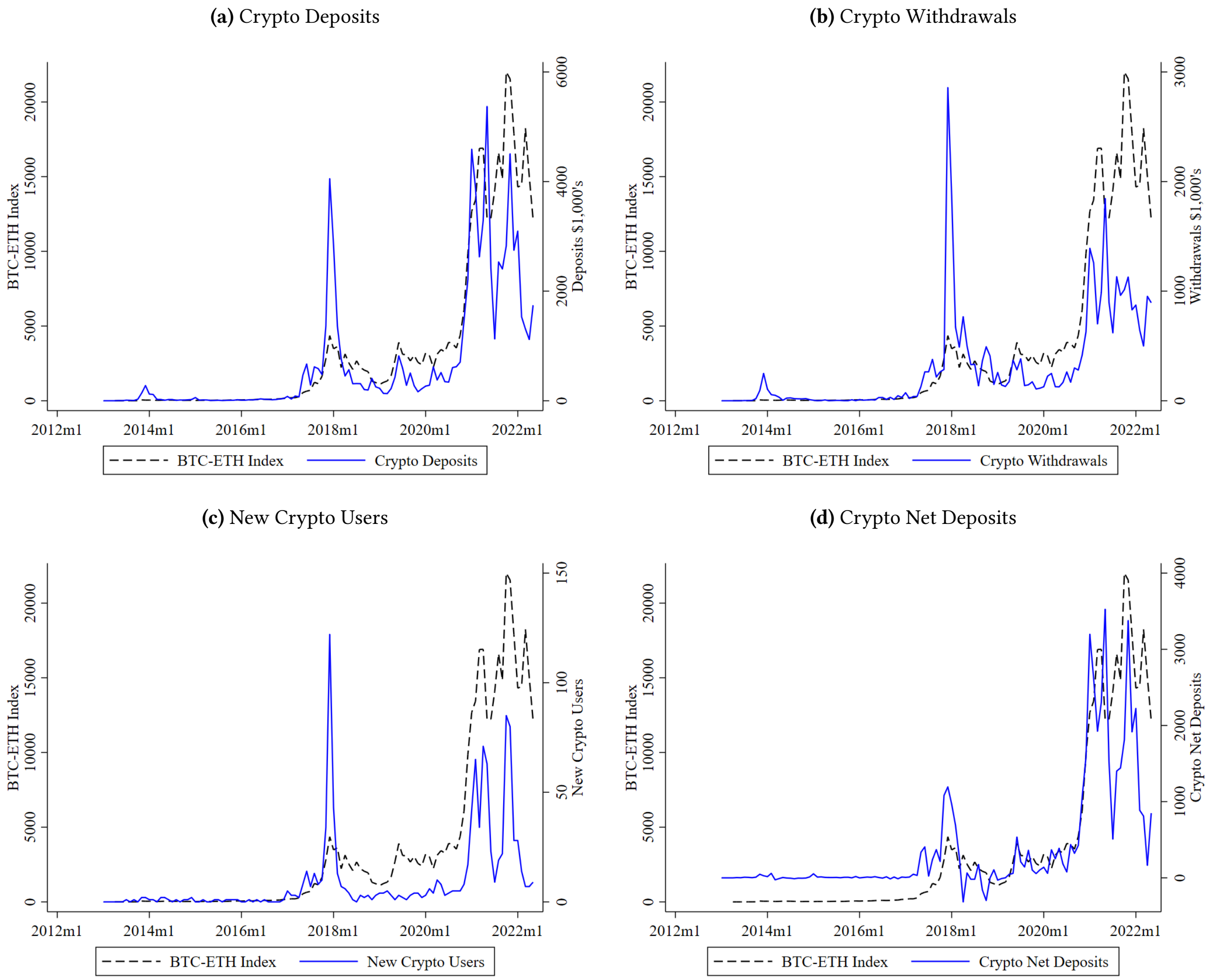


Figure 3. Crypto Adoption and Crypto Portfolio Activity. This figure shows the relation between retail crypto activity and a value-weighted Bitcoin-Ethereum index. Figure (a) depicts flows of deposits into cryptocurrencies. Figure (b) shows withdrawals or redemption of crypto. Figure (c) shows the number 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.

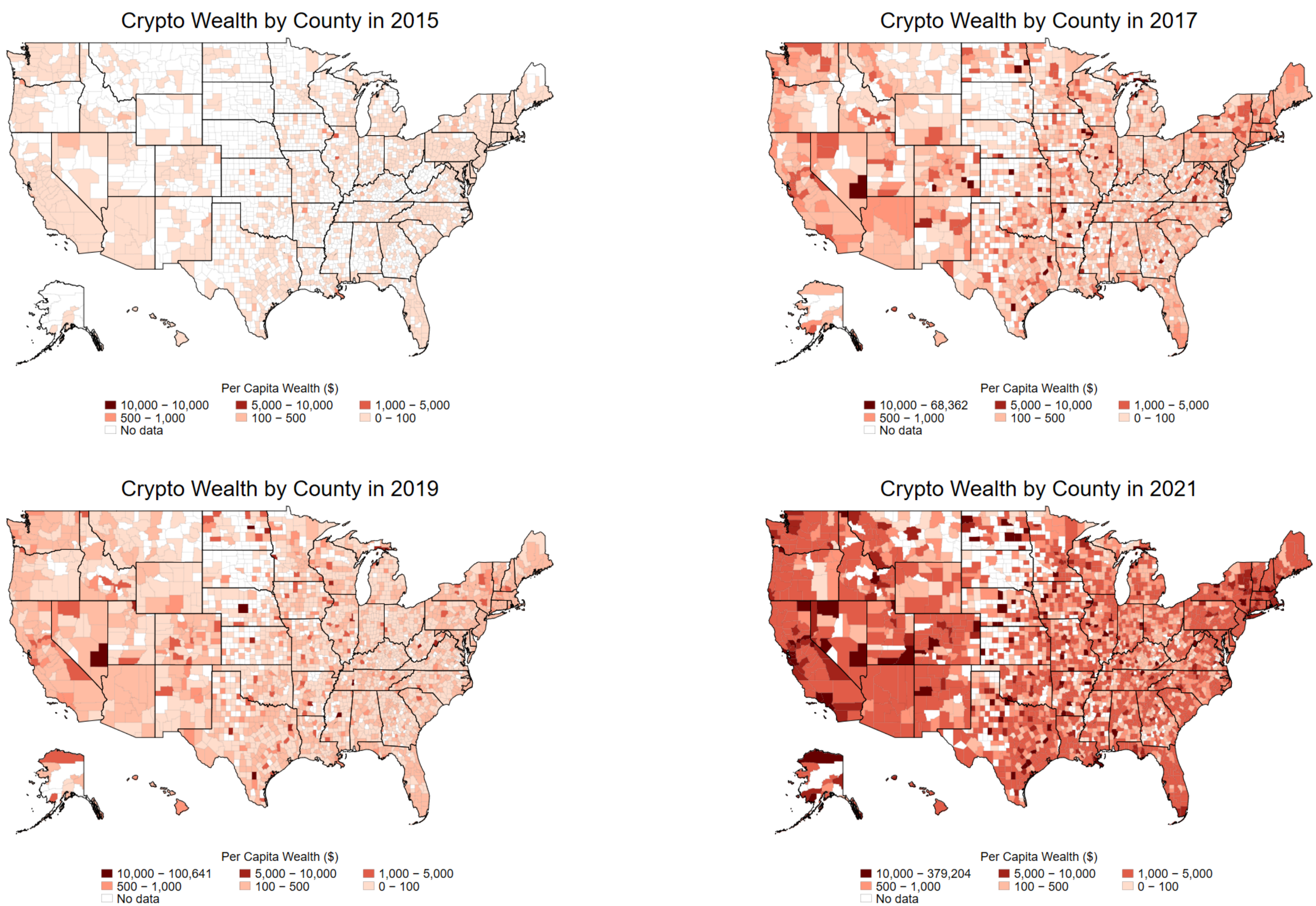


Figure 4. Crypto User Geography over Time. This figure shows the geographic evolution of crypto activity over time. We identify transactions to cryptocurrency exchanges and assume that deposits and withdrawals represent either buying or selling into a value-weighted Bitcoin-Ethereum index at that day's 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.

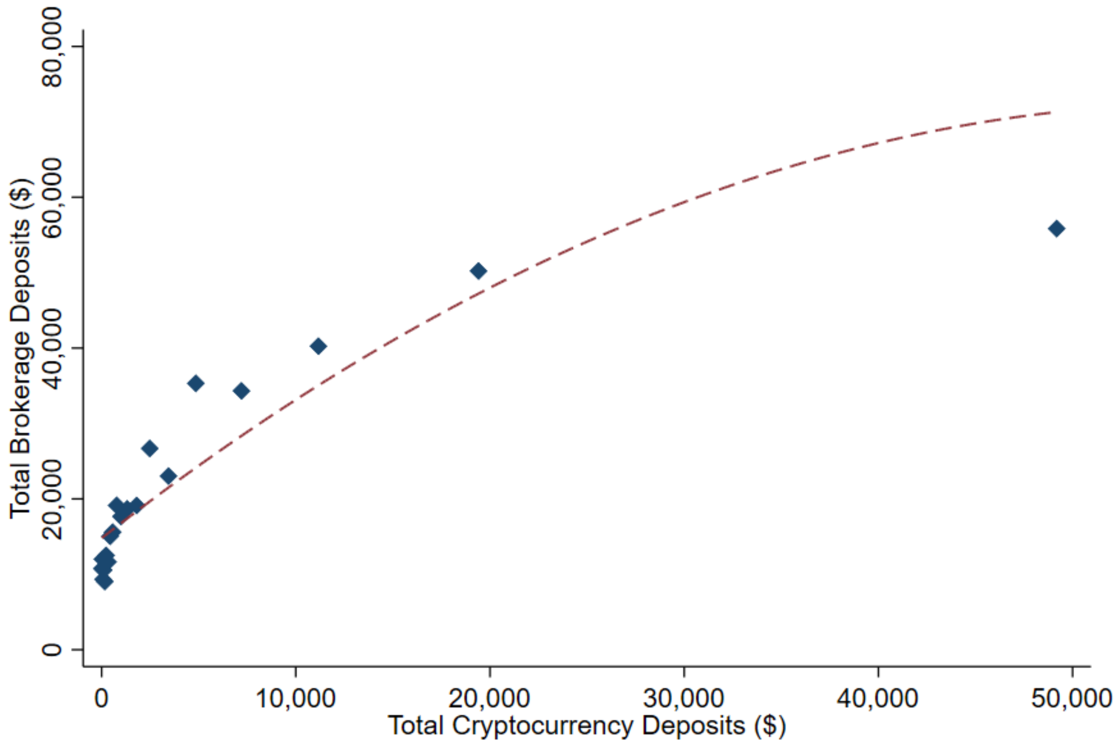


Figure 5. Cryptocurrency Deposits and Equity Investments. This figure depicts a cross-sectional bin-scatter plot with a quadratic fitted line of total deposits to brokerages against total cryptocurrency exchange deposits. Underlying data are at a user level. We limit the plot to users who have cumulatively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

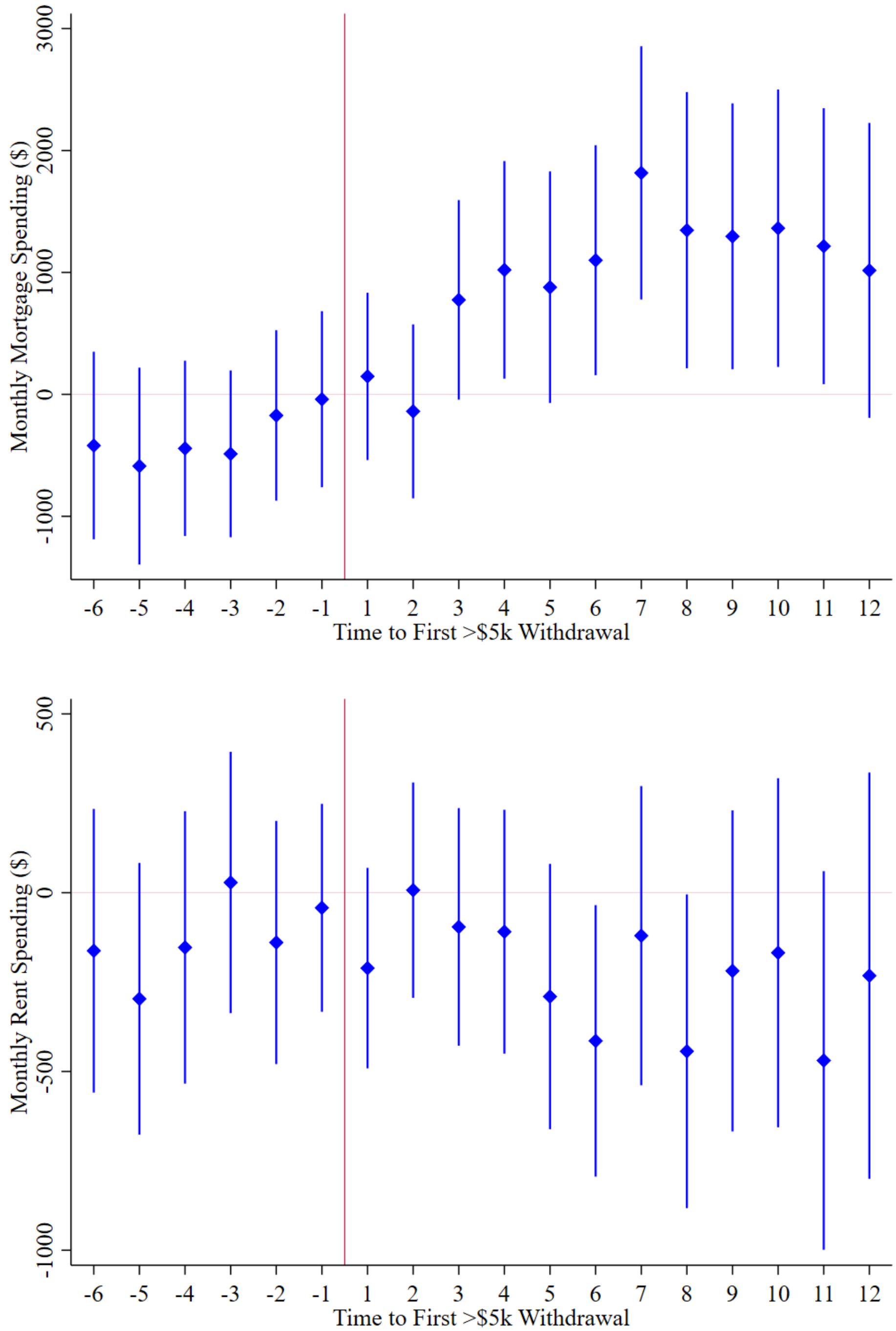
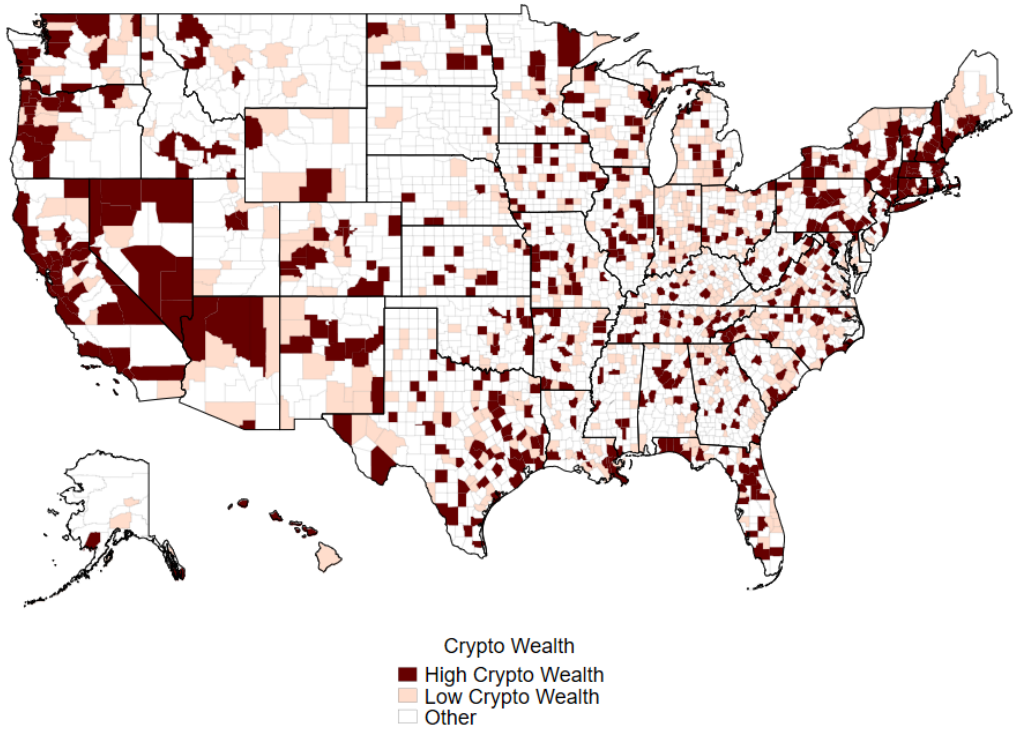
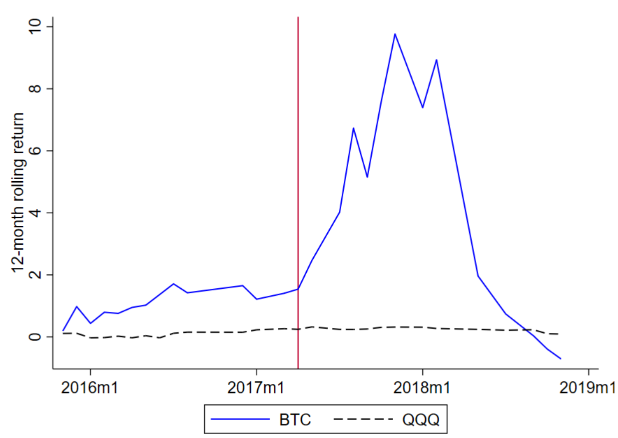


Figure 6. Monthly Mortgage and Rent Spending Around First Large Bitcoin Withdrawal. Each panel plots the coefficients on an event-study regression for the months before and after a user first withdraws at least $5,000 from a cryptocurrency exchange. The top panel shows monthly mortgage spending around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

(a) Crypto Wealth by County



(b) Bitcoin Returns



(c) Crypto Withdrawals

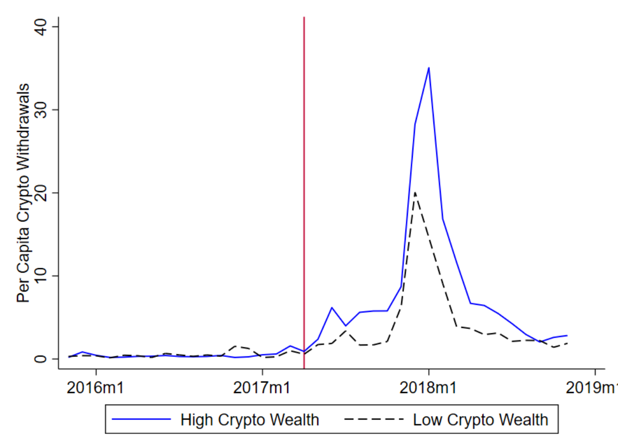


Figure 7. Crypto County Wealth and Withdrawals during the Bitcoin Run-up. The map in Panel (a) highlights counties that have per capita crypto wealth in the top tercile (dark red) and bottom tercile (light pink) as of December 2016; these are the treated and control counties in our difference-in-difference 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.

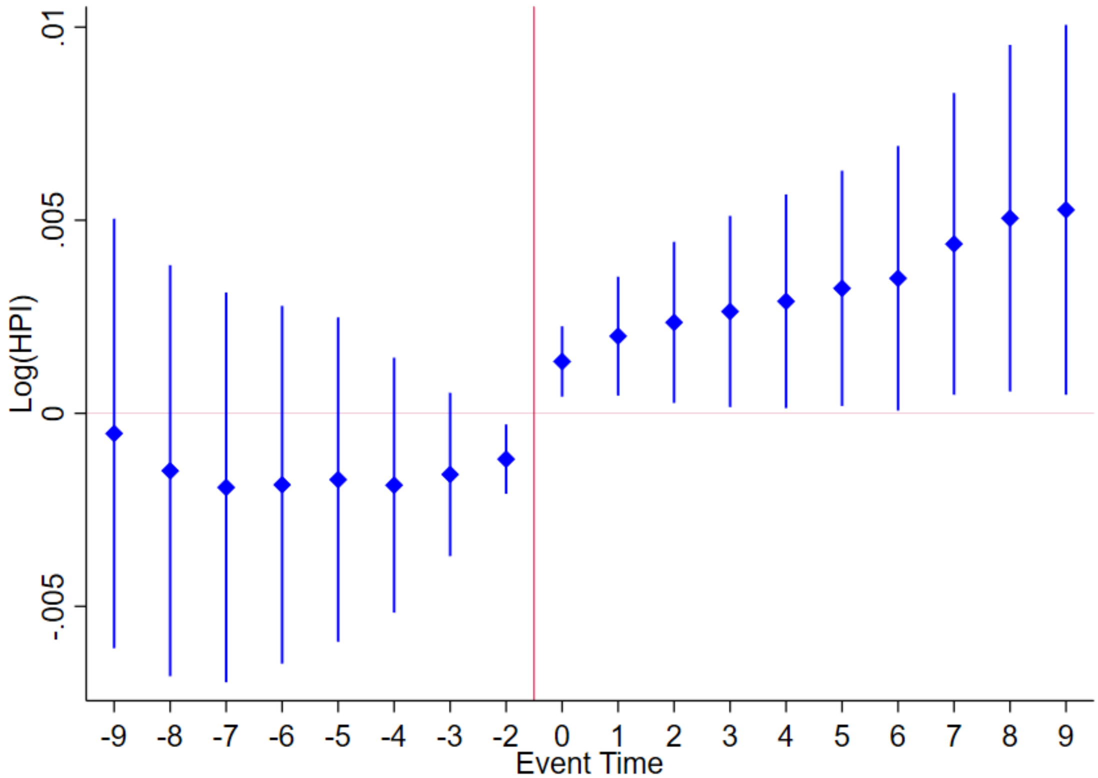


Figure 8. The Bitcoin Run-Up Diff-In-Diff. This figure shows our difference-in-differences analysis of the aggregate effect of county-level crypto wealth on county-level house prices in event time. The y-axis is Log(Median County House Price). Treated (control) counties are defined as counties that are 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 3–6. This panel focuses on the pre-Covid sample from 2015–2019, and includes both crypto adopters and non-crypto adopters. Panel B summarizes the sample used in the crypto withdrawal event study in Table 7 and 8. 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 2014–2022. Panel C summarizes the county-level sample used in our difference-in-differences analysis in Table 9, 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 10. This sample is estimated over the full sample from 2014–2022.

Variable	Obs.	Mean	Std. Dev.	Q5	Q25	Q50	Q75	Q95
Panel A: MPC Household-level Sample								
Total Quarterly Spending	1,837,840	14,653	12,838	2,192	6,543	11,415	18,772	37,489
Total Quarterly Income	1,830,868	20,296	16,392	1,775	9,001	16,085	26,947	53,750
Conditional on Crypto User								
Avg. Quarterly Crypto Gains	60,268	393	3,204	-798	-38	1	79	1,994
Cumulative Crypto Deposits	60,268	10,971	28,103	59	465	1,982	8,085	50,578
Crypto Wealth	60,268	6,030	41,100	0	55	336	1,802	19,613
Crypto Exit	55,739	0.012	0.111	0	0	0	0	0
Panel B: Household-level Withdrawal Event Sample								
Total Monthly Spending, Annualized	27,286	84,838	88,145	6,283	31,905	61,325	106,760	239,698
Lagged Monthly Income	27,286	11,421	8,919	302	5,190	8,999	15,517	30,008
New Homeowner Indicator	27,286	0.108	0.311	0	0	0	0	1
Crypto Withdrawal >$5,000	1,873	17,038	24,325	5,257	6,874	9,923	17,060	50,000
Panel C: County-level Diff-in-Diff Sample								
Median County House Price	28,043	183,193	118,606	71,806	109,672	154,158	218,864	392,744
Log(Median County House Price)	28,043	12.0	0.5	11.2	11.6	11.9	12.3	12.9
Annual House Price Growth (pp)	28,043	4.9	4.0	-1.2	2.6	4.9	7.3	11.1
Log(County Crypto Wealth per capita, Dec. 2016)	28,043	2.3	1.5	0.0	1.2	2.3	3.2	4.8
Panel D: County-level 2SLS Sample								
Median County House Price	165,258	188,090	126,777	69,967	110,588	155,706	226,657	408,710
3-month Change in Median County House Prices	165,258	4,409	6,189	-606	1,345	2,907	5,544	14,408
6-month Change in Median County House Prices	156,942	8,584	11,156	-360	2,964	5,848	10,615	26,743
Annual per capita County Crypto Gains	165,258	403	3,211	-134	1	32	211	1,741

Table 2

Summary Statistics of Sample and Crypto Users

This table shows sample means 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. ***, **, 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	8,176	7,356	821***
Total Spending	5,293	5,105	188***
Traditional Investment	241	131	110***
Crypto Investment	78	0	78***
Crypto Gains	114	0	114***
Percent of Spending:			
AutoFuel	5.2	4.7	0.5***
Cable/Telecom	6.0	6.2	-0.2***
Cash/Check	17.8	21.1	-3.2***
Charity	0.5	0.5	0.1
Education	0.4	0.3	0.1
Entertainment/Travel	7.4	6.3	1.1***
General Merchandise	21.6	21.4	0.2
Groceries	8.8	9.0	-0.2**
Insurance	4.9	5.1	-0.2***
Medical	1.8	2.1	-0.2***
Mortgage	9.9	9.2	0.7***
Rent	2.1	1.7	0.4***
Restaurants	9.7	8.5	1.1***
Utilities	3.8	3.9	-0.1***

Table 3

Crypto Gains and Investment

This table tests the sensitivity of crypto and equity investments to gains in crypto wealth. The primary independent variable is the average quarterly change in crypto wealth defined in Equation 2. The dependent variable in column (1) is the sum of 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) use the entire sample of users. Column (3) uses a subsample restricted to crypto users. 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	0.0602***	0.0294***	0.0876***
	(12.23)	(6.23)	(9.29)
Lagged Crypto Deposits	0.298***		0.0653***
	(26.32)		(6.82)
Lagged Investment Deposits		0.171***	
		(40.28)	
Lagged Income Control	X	X	X
Household FE	X	X	X
State × Quarter FE	X	X	X
Sample	Full	Full	Full
Observations	2,536,916	2,536,916	136,482
Adjusted R^2	0.172	0.289	0.124

Table 4

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. *Avg. Quarterly Crypto Gains* is the average quarterly change in crypto wealth over the prior year defined in Equation 2. *Covid* is an indicator equal to 1 for observations in 2020 or later. *Negative Gains* is an indicator equal to 1 if the average quarterly gain in the last year is negative. 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) are estimated using the entire sample from 2015-2022. Columns (3)–(5) use the pre-Covid period prior to 2020. Columns (4) and (5) 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.

	Total Quarterly Spending				
	OLS	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
Avg. Quarterly Crypto Gains	-0.00298	0.0917***	0.0975***	0.0786***	0.0928***
	(-0.25)	(4.12)	(4.41)	(3.59)	(3.42)
Avg. Quarterly Crypto Gains × Covid Indicator		-0.117***			
		(-4.60)			
Avg. Quarterly Crypto Gains × Negative Gains Indicator					-0.128
					(-1.45)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
State × Quarter FE	X	X	X	X	X
Sample	Full	Full	Pre-Covid	Pre-Covid	Pre-Covid
Observations	2,536,916	2,536,916	1,837,840	1,837,840	1,837,840
Adjusted R^2	0.687	0.687	0.725	0.054	0.055
Weak ID KP F Stat				2,546	1,731

Table 5

Heterogeneous Effects

This table shows consumption sensitivity to crypto wealth by income quartiles. The dependent variable is the household's total spending in the quarter. *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. Panel A presents estimates of the overall effect of crypto gains on consumption, while Panel B shows the interaction of *Negative Gains*, an indicator equal to 1 if the average quarterly gain in the last year is negative, with crypto gains. 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.

Panel A

	Quarterly Spending by Income Quartile			
	1st	2nd	3rd	4th
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Avg. Quarterly Crypto Gains	0.00849	0.0651	0.0764**	0.104**
	(0.37)	(1.25)	(2.16)	(2.36)
Lagged Income Control	X	X	X	X
Household FE	X	X	X	X
State × Quarter FE	X	X	X	X
Sample	Pre-Covid	Pre-Covid	Pre-Covid	Pre-Covid
Observations	492,287	465,965	453,045	421,120
Adjusted R^2	0.108	0.074	0.055	0.035

Panel B

	Quarterly Spending by Income Quartile			
	1st	2nd	3rd	4th
	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Avg. Quarterly Crypto Gains	0.0403	0.0630	0.0798*	0.123**
	(1.52)	(1.02)	(1.80)	(2.20)
Avg. Quarterly Crypto Gains	-0.259*	0.0219	-0.0304	-0.162
× Negative Gains Indicator	(-1.79)	(0.13)	(-0.23)	(-0.84)
Lagged Income Control	X	X	X	X
Household FE	X	X	X	X
State × Quarter FE	X	X	X	X
Sample	Pre-Covid	Pre-Covid	Pre-Covid	Pre-Covid
Observations	492,287	465,965	453,045	421,120
Adjusted R^2	0.108	0.074	0.055	0.035

Table 6

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	0.0786***	0.00354	0.000131	0.0622***	0.000614
	(3.59)	(1.57)	(0.16)	(3.57)	(0.47)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
State × Quarter FE	X	X	X	X	X
Sample	Pre-Covid	Pre-Covid	Pre-Covid	Pre-Covid	Pre-Covid
Observations	1,837,840	1,837,840	1,837,840	1,837,840	1,837,840
Adjusted R^2	0.054	0.006	0.011	0.018	0.000
	Quarterly Spending				
	Education	Entertain/Travel	General Merch.	Groceries	Insurance
	2SLS	2SLS	2SLS	2SLS	2SLS
	(6)	(7)	(8)	(9)	(10)
Avg. Quarterly Crypto Gains	0.00199	-0.000599	0.00287	0.00263	-0.00118
	(1.10)	(-0.18)	(0.67)	(1.44)	(-0.84)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
State × Quarter FE	X	X	X	X	X
Sample	Pre-Covid	Pre-Covid	Pre-Covid	Pre-Covid	Pre-Covid
Observations	1,837,840	1,837,840	1,837,840	1,837,840	1,837,840
Adjusted R^2	-0.000	0.007	0.025	0.012	0.005
	Quarterly Spending				
	Medical	Mortgage	Rent	Restaurants	Utilities
	2SLS	2SLS	2SLS	2SLS	2SLS
	(11)	(12)	(13)	(14)	(15)
Avg. Quarterly Crypto Gains	-0.00169*	0.00894*	0.00106	-0.00180	-0.0000316
	(-1.86)	(1.70)	(0.47)	(-1.17)	(-0.02)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
State × Quarter FE	X	X	X	X	X
Sample	Pre-Covid	Pre-Covid	Pre-Covid	Pre-Covid	Pre-Covid
Observations	1,837,840	1,837,840	1,837,840	1,837,840	1,837,840
Adjusted R^2	0.003	0.008	0.001	0.016	0.007

Table 7

Crypto Withdrawals and Expenditures

This table presents event study regressions at the household-month level for a sample of crypto users. The event is defined as the first time a household takes a withdrawal from a crypto exchange greater than $5,000. These withdrawal events span the entire sample from 2014–2022, 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	7876.8***	319.3***	13.71	2521.8**	38.02
	(5.18)	(3.04)	(0.27)	(2.01)	(0.78)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	27,286	27,286	27,286	27,286	27,286
Adjusted R^2	0.536	0.338	0.582	0.343	0.579
	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	-162.9	452.9**	2742.7***	328.3***	183.1**
	(-0.94)	(2.34)	(7.75)	(3.35)	(2.19)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	27,286	27,286	27,286	27,286	27,286
Adjusted R^2	0.257	0.421	0.496	0.618	0.506
	Monthly Spending, Annualized				
	Medical	Mortgage	Rent	Restaurants	Utilities
	OLS	OLS	OLS	OLS	OLS
	(11)	(12)	(13)	(14)	(15)
Post First Crypto Withdrawal >$5,000	97.53*	601.7**	120.2	478.7***	141.9**
	(1.69)	(2.23)	(0.98)	(3.88)	(2.16)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	27,286	27,286	27,286	27,286	27,286
Adjusted R^2	0.336	0.719	0.544	0.557	0.536

Table 8

Crypto Withdrawals and Transition into Homeownership

This table presents event study regressions similar to those of Table 7 but focusing on mortgage spending and new home ownership. Columns (1) and (3) define an event as a first crypto exchange 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 Spending Annualized		New Homeowner	
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Post First Crypto Withdrawal >$5,000	601.7**		0.0379***	
	(2.23)		(4.16)	
Post First Crypto Withdrawal >$10,000		731.8*		0.0466***
		(1.96)		(3.66)
Lagged Income Control	X	X	X	X
Household FE	X	X	X	X
Year FE	X	X	X	X
Observations	27,286	14,641	27,386	14,689
Adjusted R^2	0.719	0.703	0.299	0.311

Table 9

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, as well as county and 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	0.00463**		1878.1***	
	(2.19)		(2.87)	
Log County Crypto Wealth × Post Run-up		0.00189**		648.7***
		(2.34)		(2.94)
12-Month Lagged Outcome	X	X	X	X
County FE	X	X	X	X
Month FE	X	X	X	X
Observations	18,285	28,043	18,285	28,043
Adj. Within R^2	0.232	0.127	0.508	0.551

Table 10

Effect of Crypto Gains on Housing Prices

This table presents instrumental variable estimates of the effect of county-level crypto gains on county house prices. In columns (1)–(4), 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 columns (5) and (6), 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 2022. All specifications include a control for the change in county house prices over the prior quarter, as well as county and month fixed effects. 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		Change in House Price Index		Change in House Price Index	
	Next 3 Months	Next 6 Months	Next 3 Months	Next 6 Months	Next 3 Months	Next 6 Months
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Per Capita Crypto Gains, Prior 12-Months	0.0510*	0.161*	0.0780**	0.232**	0.0699**	0.219**
	(1.87)	(1.94)	(2.21)	(2.10)	(2.22)	(2.10)
Δ House Price Index, Prior 3-Months	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
County FE			X	X	X	X
Instrumental Variable	Passive Gains		Passive Gains		Excess Passive Gains	
Observations	165,267	157,102	165,258	157,088	165,258	157,088
Weak ID KP *F* Stat	4,347	8,209	1,401	7,949	1,388	5,256

Internet Appendix

A.1 Internet Appendix

Internet Appendix

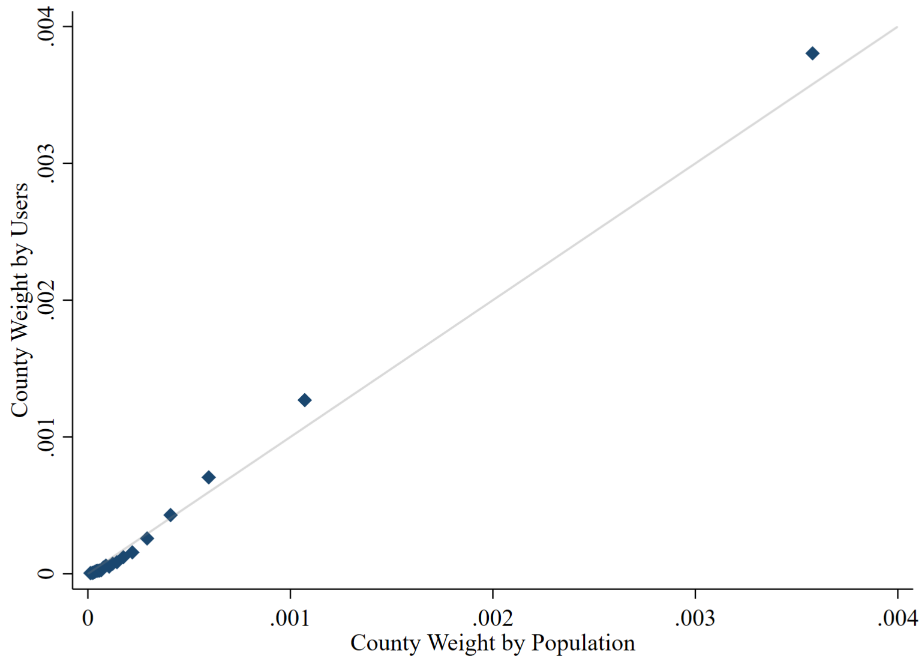


Figure A.1. County Weights by Population vs. Transaction Users This figure shows a binscatter of county weights based on county population vs county weights based on the number of households in our transaction database.

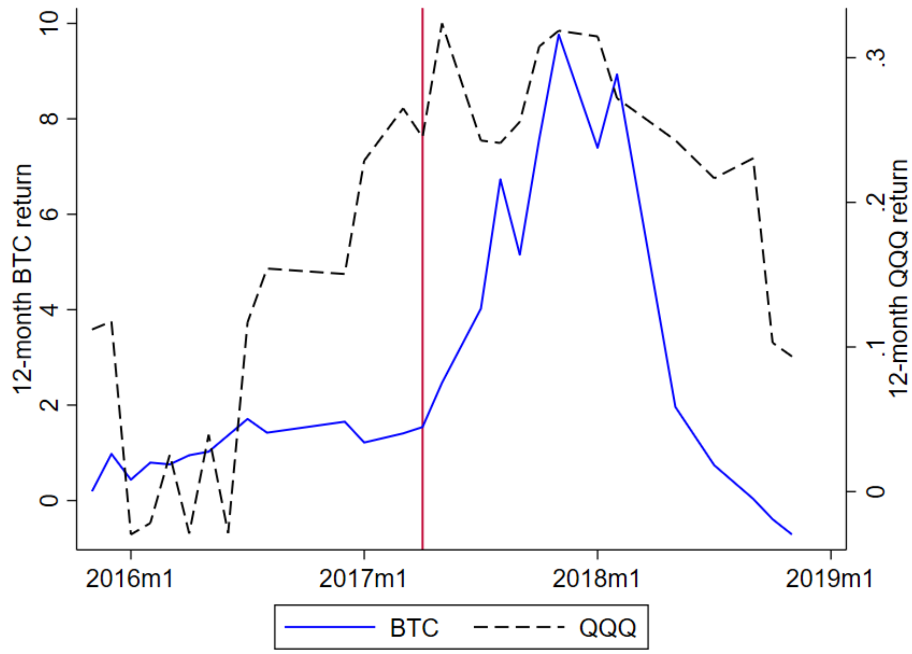


Figure A.2. Bitcoin and Nasdaq Rolling 12-month Returns. This figure shows the 12-month holding period returns each month for holding Bitcoin and the Nasdaq (QQQ). The figure plots the returns on separate axes, with Bitcoin returns on the left axis. The red line in the figures indicates the pre- and post-periods used in our difference-in-differences analysis reported in Table 9, which we define based on the beginning of the Bitcoin price run-up.

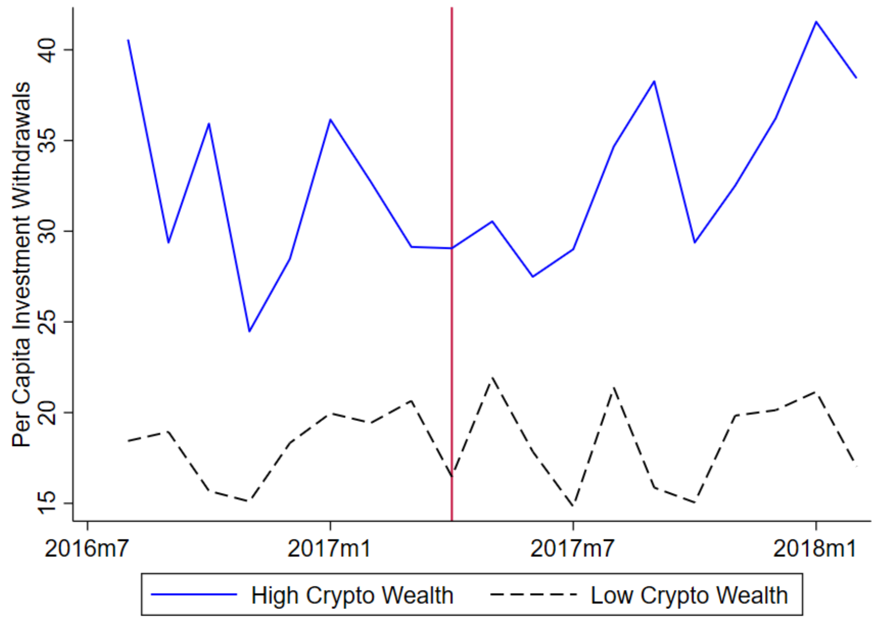


Figure A.3. Equity Investment Withdrawals around Bitcoin Run-up by Crypto Wealth. This figure shows county-level per capita withdrawals from traditional brokerages each month separately for high and low crypto wealth counties. High (low) crypto wealth counties are defined based on the top (bottom) tercile 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 9, which we define based on the beginning of the Bitcoin price run-up.

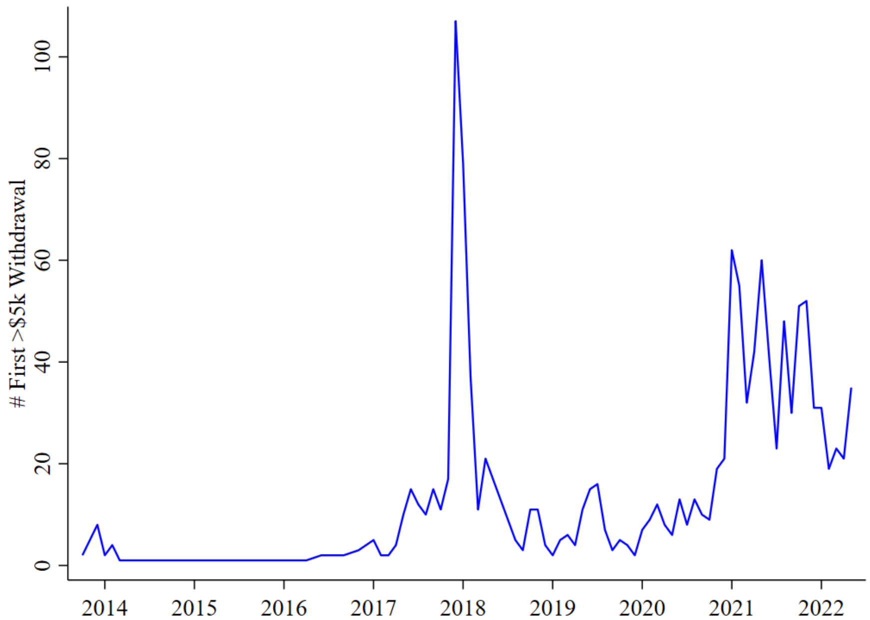


Figure A.4. Large Crypto Withdrawals. This figure shows the number of first time large crypto withdrawals (greater than $5,000) each month for our sample of crypto users. We use this sample in our withdrawal event study reported in Table 7.

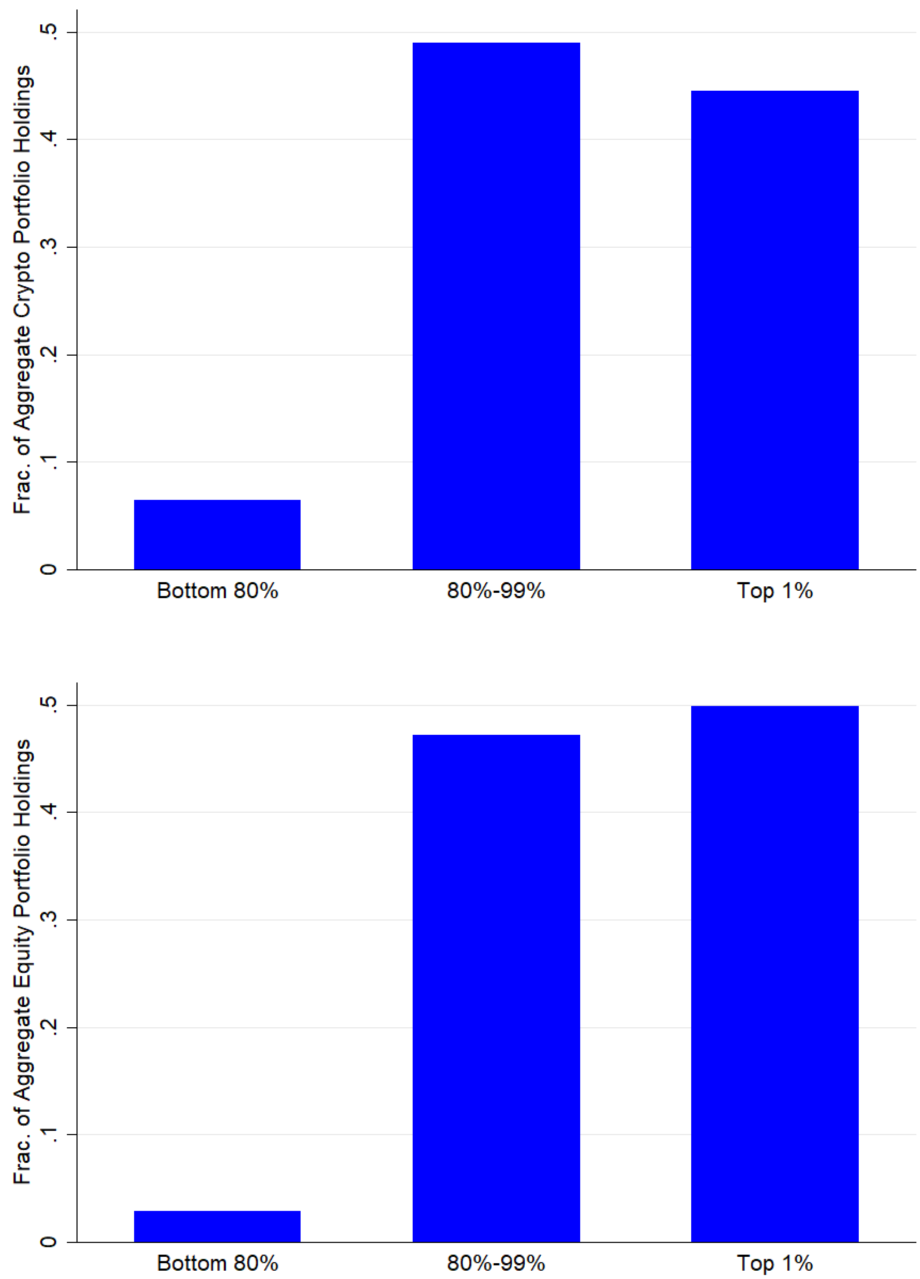


Figure A.5. Distribution of Investment Wealth. These figure show the distribution of investment wealth. The top figure presents the distribution of total crypto portfolio values as of December 2021 for our sample of crypto users. The bottom figure shows the distribution of equity portfolio values for U.S. households based on the 2016 Survey of Consumer Finances (SCF).

Table A.1

Effect of Crypto Gains on Housing Prices—2SLS Breakdown

This table reports results related to columns (3) and (5) of Table 10. Column (1) presents the OLS (uninstrumented) relationship between crypto gains and housing prices, columns (2) and (4) present the reduced form versions of columns (3) and (5) of Table 10, respectively, and columns (3) and (5) present the relevant first stages for columns (3) and (5) of Table 10. Observations are at the county-month level starting in 2015 and ending in 2022. Controls and fixed effects are included as indicated. *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	Change in House Price Index, Next 3 Months	Per Capita Crypto Gains, Prior 12 Months	Change in House Price Index, Next 3 Months	Per Capita Crypto Gains, Prior 12 Months
	OLS	RF	FS	RF	FS
	(1)	(2)	(3)	(4)	(5)
Per Capita Crypto Gains, Prior 12-Months	0.0773**				
	(2.53)				
Passive Gains		0.0806**	1.033***		
		(2.18)	(37.43)		
Excess Passive Gains				0.0781**	1.117***
				(2.22)	(37.26)
Δ House Price Index, Prior 3-Months	X	X	X	X	X
Month FE	X	X	X	X	X
County FE	X	X	X	X	X
Observations	165,258	165,258	165,258	165,258	165,258
Adj. R^2	0.758	0.758	0.906	0.758	0.907

Table A.2

Effect of Crypto Gains on Housing Prices—Lagged IV

This table presents instrumental variable estimates of the effect of crypto gains on house prices. We instrument for county-level per capita crypto gains with *Lagged Passive Gains* and *Lagged Excess Passive Gains*. These instruments are defined similarly to the instruments in Table 10, but use county-level per capita crypto wealth as of 24-months prior to the focal observation, rather than 12-months prior, multiplied by the value-weighted Bitcoin and Ethereum return (or excess return) over the prior 12-months. Observations are at the county month level starting in 2015 and ending in 2022. Controls and fixed effects are included as indicated. 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		Change in House Price Index		Change in House Price Index	
	Next 3 Months	Next 6 Months	Next 3 Months	Next 6 Months	Next 3 Months	Next 6 Months
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Per Capita Crypto Gains, Prior 12-Months	0.0372	0.139*	0.0669*	0.205*	0.0573*	0.179*
	(1.50)	(1.77)	(1.85)	(1.90)	(1.71)	(1.80)
Δ House Price Index, Prior 3-Months	X	X	X	X	X	X
Month FE	X	X	X	X	X	X
County FE			X	X	X	X
Instrumental Variable	Lagged Passive Gains		Lagged Passive Gains		Lagged Excess Passive Gains	
Observations	133,399	125,505	133,387	125,498	133,387	125,498
Weak ID KP F Stat	147.7	118.3	198.3	158.4	193.4	165.8