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, investment, and local real estate markets. We estimate an MPC out of unrealized crypto gains of $0.21, mostly driven by increases in discretionary consumption. In contrast, households sell crypto to increase both equity investment as well as housing spending. As a result, crypto wealth causes house price appreciation—counties with higher crypto exposure experience higher growth in home values following high Bitcoin 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, household balance sheet, real estate.

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*All errors are our own responsibility.

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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 strategy and crypto's extreme volatility has led to rapid wealth gains for some investors. Despite this, relatively little attention has been paid to the role that the introduction of this asset class has had on the investment and consumption behavior of individual households or its effect on other asset prices. While public blockchains provide unparalleled transparency for crypto transactions themselves, the anonymous nature of these transactions has made them a particularly difficult topic to study relative to other aspects of household financial decisions.

In this paper, we use transaction-level data from millions of U.S. households' bank accounts and credit card payments to study household consumption responses 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 infer 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 find that crypto users are likely to sell crypto and increase spending across many categories following high Bitcoin returns. Qualitatively, this mirrors consumption responses to the appreciation of other asset classes such as housing (e.g., Carroll, Otsuka, and Slacalek (2011) and Aladangady (2017)) and equities (e.g., Hartzmark and Solomon (2019) and Di Maggio, Kermani, and Majlesi (2020)). Following high Bitcoin returns, the largest change in spending comes from higher mortgage expenses. Aggregated to the county-level, greater cryptocurrency exposure drives faster house price growth following periods of high Bitcoin returns.

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, Kotter, and Williams (2023). In this paper, we focus primarily on the effect of crypto gains on consumption and investment decisions. We find that crypto adopters are wealthier and more likely to deposit money in traditional equity brokerages than non-adopters. Consistent with these wealth 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 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 categorical spending patterns change following the large run-up in Bitcoin prices in late 2017. On average, we estimate a marginal propensity to consume (MPC) out of crypto wealth of \$0.21. This rate of spending is large and approaches 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 Bitcoin gains more like an exogenous cash flow shock than like a traditional portfolio investment. The estimated MPC is smaller than those found in studies of lottery winnings, which range from 50% to nearly 100%

(Fagereng, Holm, and Natvik, 2021).

The MPC out of crypto wealth gains differs markedly across investors. Investors with the largest gains (top 1%) have MPCs closer to 0.04, a rate comparable to spending out of other asset classes like equities or housing wealth (Di Maggio, Kermani, and Majlesi, 2020; Aladangady, 2017). Moreover, the largest 1% of crypto portfolios by crypto wealth tend to hold in excess of 40% of the total crypto wealth, meaning that the dollar weighted marginal propensity to consume out of gains falls well below a household-weighted measure. The near-term MPC out of crypto wealth is mostly driven by higher discretionary spending, and, consistent with some survey evidence (Benetton and Compiani, 2022), is larger for later adopters and for households facing liquidity constraints.

Because consumption following realized gains might differ from consumption out of largely unrealized gains, we also examine consumption changes around large crypto withdrawal events. In these household event studies, we find little evidence of changes to discretionary spending following withdrawals, but large increases in housing spending such as mortgage payments, utilities, and insurance. We further show that large crypto withdrawals are associated with a transition into new homeownership, as well as significantly higher mortgage payments for existing homeowners. That is, households with realized crypto gains often utilize a portion of these gains to finance additional housing consumption.

These individual-level changes in housing consumption suggest that crypto returns could potentially spill over into the 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 (including crypto and housing). 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 crypto exposure prior to 2017 (measured as per capita wealth in December 2016) were highly exposed to a quasi-random 12-month Bitcoin return of over 1,400%. Consequently, we observe much higher withdrawals of crypto wealth from these counties at the beginning of 2018. We use a difference-in-differences methodology to compare the house price growth between counties with different exposure, before and after the large Bitcoin run-up. By fixing crypto exposure in the pre-period, this set-up eliminates concerns of reverse causality.

For this difference-in-differences specification to identify the causal effect of crypto wealth on local house prices, we must assume that absent the large Bitcoin price run-up, house prices would have evolved similarly in counties with different levels of exposure to crypto. In support of this parallel trends assumption, we show that house prices in high- and low-crypto exposure counties were similar in the months prior to the Bitcoin price run-up. We further show that high crypto exposure counties experience a sharp increase in crypto withdrawals following the crypto wealth shock, but experience no discontinuous change in traditional brokerage withdrawals. In contrast, low crypto exposure counties experience a markedly reduced jump in withdrawals of either crypto or equities. This similarity in pre-period trends, combined with the quasi-random timing of the Bitcoin price shock and the lack of any equity market response, make it plausible that this set-up identifies the causal effect of crypto wealth on house prices.

Using this difference-in-differences experiment, we find significantly higher house price appreciation for counties that had high pre-2017 per capita crypto wealth in the months following the price run-up. House prices in high crypto exposure counties grow about 3 basis points faster than house prices in low exposure counties. This explains roughly 8% of the standard deviation in house price growth during this time period, suggesting that crypto wealth has a meaningful impact on the local economy.

We extend the concept underlying the difference-in-differences estimation to the full time series using a two-stage least squares (2SLS) specification. 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, as an instrument for the growth in the county's crypto wealth. Because this instrument is based on historical crypto portfolios, similar to the difference-in-differences analysis, it alleviates concerns about reverse causality. 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 Bitcoin returns makes it unlikely that most sources of wealth are simultaneously correlated with crypto returns and historical crypto exposure. The most plausible exception is equity market returns. Counties with high crypto exposure 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 Bitcoin returns in excess of the equity return, alleviating concerns that equity market returns drive our results. 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 crypto wealth increases county house prices by about $0.40 over the following year.

Our paper contributes to the literature on the characteristics of cryptocurrency investors. For example, Hackethal, Hanspal, Lammer, and Rink (2022) use administrative data from a German bank to document the characteristics and changes in trading behavior of crypto users while Benetton and Compiani (2022) develops survey-based measures of expectations and beliefs of crypto investors. Chava, Hu, and Paradkar (2022) identify regional interest in cryptocurrency using google trend data and find relatively higher attention in areas where gambling sales are high and in generally more affluent regions. Divakaruni, Zimmerman, et al. (2021) use proprietary data on Bitcoin trades (via Kaiko) to document increased crypto trading following economic stimulus payments in 2020. Makarov and Schoar (2021) build a data set of Bitcoin users to describe the network, concentration, and composition of large Bitcoin traders and miners.

In contrast to these papers, our data allow us to describe a broad set of U.S. retail crypto traders and to link these traders to financial transactions, shedding further light on the factors that influence adoption. 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. While we do not observe actual trades, our data has the advantage of containing consumption transactions, allowing us to provide new insights into how crypto wealth impacts consumption decisions and the effects that these decisions have on the real economy.

Our paper also contributes to a large literature that assesses the impact of investment wealth 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 significantly lower than out of dividends. Case, Quigley, and Shiller (2005), Aladangady (2017), and Berger, Guerrieri, Lorenzoni, and Vavra (2018) look at consumption responses to changes in home values and broadly find lower MPC out of housing wealth than from dividends and roughly in line with capital gains. Even more broadly, there is a large body of work that assesses the MPC out of income or tax rebate shocks (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.

The papers that are closest to ours in nature assess the impact of regional wealth shocks stemming from traditional equity markets. Chodorow-Reich, Nenov, and Simsek (2021) use regional heterogeneity in equity wealth combined with local labor market composition to estimate how equity wealth affects consumption. Hartman-Glaser, Thibodeau, and Yoshida (2018) look at the effect of local initial public offerings (IPOs) on home values. Our paper uses regional wealth shocks induced by a highly volatile asset class to assess the impact on both consumption and home values. Additionally, we make use of micro-level data to establish the impact of liquidated crypto wealth (as opposed to paper gains) on household decisions and then identify the channel through which crypto wealth affects local house price appreciation.

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 a 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. Attrition is minimal and, once a user is in the database, the service automatically and regularly pulls data from the user's financial institutions to provide regularly updated transactions.

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 by means of the bank transfer transactions. Each individual observation from one of these accounts contains a number of pieces of information regarding that transaction. 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 automatically categorized into one of 43 different categories (e.g. salary, ATM withdrawal, groceries, mortgage and rent payments, medical spending). Merchant names and physical locations at a city or zip code level are also observable for a 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 show up in transactions. This imputed zip code represents the zip code in which they most frequently are seen making physical spending transactions in a given year.[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 across a range of fields 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 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 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.

[1] We limit these transactions to Grocery, Restaurant, Gasoline, General Merchandise, Home Improvement, and Pharmacy transactions.

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.

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 subsample of 100,652 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

[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.

with a major exchanges. These exchanges include Coinbase, Binance, Gemini, Crypto.com, Kucoin, Cryptohub, Blocket, CEX.io, and Bitstamp. Figure 2 displays a sample of transactions with crypto exchanges observed in our data.

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. The deposits are not evenly split across exchanges. Approximately 90% of the dollar flow of deposits and withdrawals across exchanges is conducted with a single exchange: Coinbase.[3] Gemini makes up another 5% of dollar flows, while the remaining exchanges make up under 5% of total dollar flows combined.

We do not observe the actual cryptocurrencies that households purchase. However, since the vast majority of crypto transactions in our data occur on the Coinbase exchange, we can gain insight into likely purchase behavior by looking at aggregate asset holdings on Coinbase. Figure 3 shows the asset mix held on Coinbase in 2019 and 2020. The vast majority—around 70%—of assets held on Coinbase are Bitcoins. Importantly, very little cash (i.e., fiat currency) is held on Coinbase. Together, this data suggests that deposits to (withdrawals from) Coinbase are most likely to represent purchases (sales) of Bitcoin. Consequently, we estimate a household's total crypto portfolio value as

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

[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.

where crypto wealth for household i on day d is equal to the household's wealth on the previous day multiplied by the daily Bitcoin return.[4] We then add net deposits to crypto exchanges on that day. This calculation assumes that all money deposited to (withdrawn from) a crypto exchange is used to purchase (sell) Bitcoin on the same day as the transaction. We further assume that initial crypto wealth is zero. We then calculate monthly crypto wealth ($\text{CryptoWealth}_{i,t}$) as the household's portfolio value on the last day of the month t.

Within our account-level sample, about 15% of households trade cryptocurrency at some point between 2014 to 2022. This is similar to the estimated share of the U.S. population that has traded crypto based on survey data.[5]

2.3 Other Data

In addition to the transaction-level data, we use several other sources of 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; we then merge in annual county-level population from the Census Bureau's Population Estimates Program. For the subset of accounts where we can impute the zip code of the home residence, we merge in zip code demographics based on the 2016-2020 ACS 5-year estimates. These zip code level characteristics include race, education, income, occupation, and industry.

For the analysis in Section 5, we aggregate cryptocurrency portfolio values to the county-month level. We merge these data with the monthly county Zillow Home Value Index (ZHVI). ZHVI is a smoothed, seasonally adjusted house price index that reflects the typical value of a house in the county-month.

[4] We obtain close of day Bitcoin index prices from the *Wall Street Journal*.

[5] 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/.

2.4 Makeup of Cryptocurrency Investors

Cryptocurrency is a rapidly growing asset class, with a global market value of nearly $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 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 4 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 Bitcoin returns. The four panels of the figure show crypto deposits, withdrawals, new users, and net deposits. The salience of large Bitcoin returns is evident. Both the number of new users and total crypto deposits spike following large run-ups in Bitcoin prices. In fact, the single largest jump in new users occurs in late 2017, following the largest 12-month Bitcoin return in our sample. Interestingly, though, withdrawals also spike around this time, suggesting that at least some households cash out their crypto gains.

We frame much of our analysis in this paper around this 2017 spike in Bitcoin prices. 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. The size of our data make it impractical to make these comparisons over the entire data, so we use a sample of 100,652 households. Within this set, about 4,886 households trade crypto at some point between 2014 and December 2017. Of these crypto adopting households, 1,370 first trade crypto before July 2017 when Bitcoin prices began to rapidly appreciate. We examine how these early crypto adopters differ from later adopters (first transaction July-December 2017), as well as how both types of crypto adopters differ from households that do not adopt crypto by the end of 2018.

In Table 1 we show the average amount of monthly income, spending, and the fraction of spending made up of various categories for early crypto adopters, late crypto adopters, and never adopters in the months surrounding the 2017 Bitcoin price run-up. A few key patterns emerge from the data. Crypto adopters have higher incomes than non-adopters: Average monthly income is \$8,747 for early adopters vs. \$7,212 for non-adopters. Aiello et al. (2023) find similar differences in income across adopters over the entire 2014–2022 time period. Perhaps unsurprisingly given the income differences, crypto adopters also invest substantially more in equities than non-adopters, both through brokerages (*Traditional Investment*) and through apps such as Robinhood or Acorns (*FinTech Investment*). Early crypto adopters have somewhat higher incomes than late adopters, but the differences are less pronounced than the differences between crypto and non-crypto users.

Despite income differences, overall spending patterns are quite similar for crypto adopters and non-adopters. There are no substantial differences in the fraction of total spending made up of auto, housing, groceries, utilities, or medical expenses. Consistent with their higher income, crypto users do spend a bit more on discretionary items. Entertainment makes up 8.1, 7.8, and 6.3 percent of spending for early adopters, late adopters, and non-adopters, respectively. Similarly, restaurant spending is about one percentage point higher for crypto users relative to non-crypto users.

Figure 5 shows how the geography of cryptocurrency wealth evolves over time. We aggregate total crypto portfolio value to the county level and divide it by county population. We then show the county maps at year-end 2015, 2017, 2019, and 2021. Early in the sample, high crypto per capita values are mostly concentrated along the coastal regions of the U.S., while much of the interior of the U.S. has no crypto exposure. Over the intervening years, crypto wealth has spread into the center of the country. By the end of 2021, most populated U.S. counties have at least some level of crypto exposure. However, the largest per capita crypto values are still mostly in counties located on the coasts or in Arizona, Colorado, and Nevada. The geographic concentration suggests the possibility that crypto wealth might 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 1 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.[6] 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

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

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. We begin by examining the correlation between total crypto investment and total traditional brokerage investment. In the top panel of Figure 6, we plot a cross-sectional bin scatter of total brokerage deposits against total cryptocurrency deposits for individuals with total cryptocurrency deposits of $10,000 or less. There is a strong, positive correlation between the two types of deposits. Households who make lots of crypto deposits also make lots of traditional brokerage deposits; however, the total amount of brokerage deposits is substantially larger than the total amount of crypto deposits. The positive correlation between crypto deposits and brokerage deposits is driven by deposits to traditional brokerages. When we separate out deposits to FinTech brokerages (Robinhood, Stash, and Acorns), we find that the correlation between crypto deposits and FinTech deposits, though positive, is quite small.

In the bottom panel of Figure 6, we remove the $10,000 restriction on total crypto deposits and see that the relationship at the high end of crypto deposits is much flatter. 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. It is plausible that these types of investors respond to crypto portfolio gains in different ways.

To explore this in more depth, we examine household investment decisions following the large run-up in Bitcoin prices in late 2017. In early December of 2017, Bitcoin prices topped $10,000 for the first time ever. 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 (see Figure 7).

Several features of this run-up in Bitcoin prices make it an attractive setting to study the effect of increases in crypto wealth on household investment and consumption decisions. First, 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 assumption that crypto users are investing solely in Bitcoin more accurate during this run-up than it is during later time periods when other crypto currencies are more developed. Second, the massive returns experienced during this run-up increase the number of households that experience meaningful increases in crypto wealth. Finally, the 2017 run-up is the first time that a large number of crypto investors experienced massive, lottery-like returns.[7] This makes it more likely that the increase in crypto wealth experienced by crypto investors during this run-up is a "shock" relative to investor expectations.[8]

For each household in our sample, we calculate crypto gains experienced during this run-up as follows:

$$\text{CryptoGains}_{i,2017} = \text{CryptoWealth}_{i,\text{Dec17}} - \text{CryptoWealth}_{i,\text{Dec16}} + \text{NetCryptoWithdrawals}_{i,2017}, \quad (2)$$

where Crypto Wealth is calculated as in Equation 1 and Net Crypto Withdrawals$_{i,2017}$ represents a household's total crypto withdrawals less total crypto deposits over 2017. Consequently, Crypto Gains includes both the realized and unrealized crypto gains experienced by the household.

There are 100,652 households in our data as of December 2017. Of these, 4,878 households invested in crypto by the end of 2017. Most of these crypto investors experienced small gains

[7]Bitcoin returns were even larger during late 2013, which pre-dates our sample data. However, the Bitcoin market was small at that point—total U.S. exchange trading volume peaked at under $60 million, versus a peak of nearly $5 billion in the 2017 run-up—and so the earlier gains were much less likely to be salient to a wide set of investors.

[8]While the 2017 Bitcoin run-up stands out, Bitcoin experienced a second large run-up in prices beginning in late 2020. Figure 7 shows that this run-up, though large, was roughly half the magnitude of the 2017 run-up. In the Internet Appendix, we replicate our analyses using this second price run-up and find qualitatively similar results.

during this run-up. Figure 8 plots histograms of the distribution of crypto gains over 2017 split up by the size of the gain. The top left figure shows the distribution of gains for users in the bottom 80th percentile of gains. A few of these investors experienced small losses, but most of these investors experienced small gains—the average gain is \$364.[9] The top right figure plots the distribution for households that experienced gains in the 80th to 99th percentile. These users experienced gains between \$3,762 and \$240,000 dollars, with an average gain of \$29,031. Finally, the bottom figure shows the distribution for the top percentile of gains. For these households, the average annual gain is \$1.3 million and the maximum gain is \$2.5 million.

The skew in crypto portfolio gains broadly matches the skew in U.S. household equity holdings. In the top panel of Figure 9, we present the total fraction of crypto portfolio values for the households in our sample as of December 2017, split up by households in the bottom 80th percentile, the 80th to 99th percentile, and the top percentile of crypto wealth. Crypto wealth is roughly evenly split between the top two categories, with very little wealth held by 80% of households. In the bottom panel of Figure 9, we plot a similar figure for household equity holdings based on the Federal Reserve's Survey of Consumer Finances (SCF). We see a very similar pattern for equity holdings—a very small fraction of total equity wealth is held by the bottom 80% of households, and the bulk of equity wealth is split evenly between the top two categories.[10] 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.

We examine the relation between crypto gains and future investment decisions by estimating

[9]Despite the massive annual returns, the volatility in Bitcoin prices made it possible to lose money in 2017 if investors bought and sold at the wrong time.

[10]The figure suggests that crypto wealth might be slightly less concentrated at the top percentile than equity wealth. However, we almost certainly underestimate the crypto wealth of the top percentile of crypto users, since these users are more likely to mine crypto and hold the proceeds in private wallets rather than crypto exchanges.

the following OLS regression:

$$y_{i,2018} = \beta\,\text{CryptoGains}_{i,2017} + \delta y_{i,2017} + \gamma\,\text{Avg.Income}_{i,2018} + \varepsilon_{i,t}. \tag{3}$$

The dependent variable, $y_{i,t}$, represents the total dollars invested by household i over 2018. We separately examine crypto investments (i.e., deposits to crypto exchanges) and traditional investments (i.e., deposits to brokerage accounts). These regressions only have one observation per household so it is not possible to include any time or household-level fixed effects. However, we include non-crypto users as a control group to absorb aggregate investment demand in 2018. We further include the lagged value of investments to control for the tendency to invest, and we include average income over 2018 to control for any simultaneous changes in income that might influence investment behavior. For our main regressions, we winsorize all variables at the 1% level and report heteroskedasticity-robust standard errors. The estimate of interest, β, represents the additional dollars invested in crypto or traditional brokerages during 2018 for each dollar of crypto gains received over the run-up in 2017.

We report the results from estimating Equation 3 in Table 2. In column (1) of Panel A, we estimate the relation between crypto gains during the Bitcoin run-up and future crypto deposits using the full sample. We find that a larger gain in crypto wealth is associated with depositing more money to crypto exchanges over the next year—a \$100 increase in crypto wealth leads to an additional \$0.62 of crypto deposits over the next year. This 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 columns (2) through (4) of Table 2, we explore the extent to which this investment behavior varies with the size of the crypto wealth shock. We use unwinsorized crypto wealth gains to split crypto users into three subsamples: households with gains less than the 80th percentile, gains between the 80th to 99th percentiles, and gains in the top percentile. We then re-estimate Equation 3 separately for each group of crypto users. In each regression, we include the full set of non-crypto users as a control group. We find that the relation between crypto gains and future crypto investment is concentrated in the 80th to 99th percentile of gains. For this set of households, the estimated effect of a $100 increase in crypto wealth is an additional $8.26 of crypto deposits. In contrast, the estimated effect of crypto wealth on future crypto investment is statistically insignificant for the bottom 80th percentile of gains, and significant but much smaller (a $100 increase in crypto wealth leads to an additional $1.38 of crypto deposits) for the top percentile of gains.

We next examine the relation between crypto wealth gains and future equity investment, proxied by deposits to traditional brokerages.[11] Panel B of Table 2 reports the results of these estimations. We find that households that experience larger gains in crypto wealth over 2017 invest more in traditional brokerages over 2018. A $100 increase in crypto wealth is associated with $1.04 of additional traditional investments. This result suggests the possibility that some households rebalance crypto gains into traditional investments. When we split the sample by the size of the crypto gain, we find that similar to future crypto investing, the results are driven by households with gains in the the 80th to 99th percentiles.

To shed more light on the possibility of portfolio re-balancing, we estimate the relation between crypto gains and future crypto withdrawals. For these regressions, we limit the sample to crypto users, since non-crypto users by definition cannot withdraw money from crypto exchanges. Panel C of Table 2 reports the results. We find a positive and significant relation between crypto gains and future crypto withdrawals, driven by households with large, but not extreme,

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

changes in crypto wealth. For these households, a $100 increase in crypto wealth is associated with $9.64 of future crypto withdrawals. Importantly, the estimates in Panel A and Panel C are driven by different households.[12] Together, the evidence across Table 2 suggests that some households exhibit momentum in crypto investing and thus double down on unrealized crypto gains. In contrast, other households realize their crypto gains in the form of withdrawals and rebalance their portfolio by depositing some of those withdrawn crypto dollars into traditional brokerages.

In the Internet Appendix, we replicate our results for the second Bitcoin price run-up that began in late 2020. We find qualitatively similar results; however, the magnitudes are generally smaller. We focus our main analysis on the first Bitcoin run-up for two primary reasons. First, as shown in Figure 7, the second run-up, though large, is roughly half the magnitude of the 2017 run-up. Second, our measure of crypto wealth is noisier in 2020 since many households are investing in currencies other than Bitcoin. Consequently, we view the 2017 run-up as a cleaner setting to measure the relation between crypto gains and household investment and consumption decisions.

4 Consumption out of Crypto Wealth

How do large increases in crypto wealth affect household consumption? We first answer this question using the 2017 Bitcoin run-up. Specifically, we re-estimate Equation 3 using total household consumption over 2018 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 3. Using the full sample, we estimate an MPC of $0.21 out of each dollar of crypto wealth. In columns (2)–(4), we examine how the MPC varies with the size of crypto gains. There is no significant effect of crypto gains on consumption for households that

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

experience low gains, a very large effect for households that receive large, but not extreme, gains, and a small effect for the top percentile of gains. This pattern is intuitive: the consumption effects are concentrated in gains that are big enough to matter—on average, equal to about 3 months of income—but not so large as to make it difficult to consume a substantial portion of the gain.

Focusing on the households that experience large, but not extreme, crypto gains, we find a MPC of $0.28 (see column (3)). This is substantially larger than the estimate of the MPC out of equity wealth, which for individuals at a similar point of the wealth distribution is 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.

Table 1 shows that early crypto investors on average deposit more money to crypto exchanges than later investors. One potential explanation for this pattern is that early crypto investors have different beliefs about crypto returns than later investors. In particular, if early investors are "true believers" in crypto, they might be less likely to consume out of their crypto gains than later adopters.

We examine this possibility in Table 4. Column (1) re-estimates the MPC out of crypto wealth for run-up adopters (i.e., households that first invest in crypto during the 2017 run-up between July and December 2017) relative to early adopters (households that first invest in crypto before July 2017). We find that run-up adopters are much more likely to consume out of the crypto wealth shock. Their MPC is about $0.46, which suggests that run-up adopters treat crypto gains more like lottery winnings Fagereng, Holm, and Natvik (2021). In contrast, early adopters treat crypto more like a traditional investment.

Another dimension in which we expect heterogeneity in consumption responses is household liquidity. Less liquid households are more likely to face consumption constraints, and, as a result, more likely to increase consumption when wealth increases. We test for this behavior using two measures of household liquidity. First, for a subset of households in our data, we observe two snapshots of bank account and credit card balances over a six-month window in 2022. Using those snapshots, combined with transaction flows, we re-create a time series of household balance sheets. We then define a liquidity-constrained household as a household that has an average bank balance of less than $1,000 over 2017. Our second measure of liquidity is based on checking account overdraft fees. We define a household as liquidity-constrained if they have one or more overdraft fees over 2017. We interact these two indicators for liquidity constraints with crypto gains in columns (2) and (3) of Table 4.

Across both measures, we find that liquidity-constrained households consume a higher fraction of their crypto gains. The MPC out of crypto wealth for liquidity constrained investors is roughly $0.51, more than double the full sample MPC.[13]

We next explore how consumption out of crypto wealth is divided across various categories. The results, reported in Table 5, show a broad increase in consumption across multiple categories. The largest effect is in spending by cash/check (see column (4)); this spending represents about 60% of the overall MPC.[14]. We also see relatively large increases in entertainment spending, general merchandise, and restaurants. The spending on these categories collectively explains about 20% of the total consumption increase following increases in Bitcoin wealth, suggesting that households respond to crypto gains by meaningfully increasing discretionary spending. Most of the remaining consumption effects come from housing spending—increases on mortgage payments, rent, and utilities.

[13]Given the noise that is inherent in imputed account balances, we focus on the magnitude from the regression using overdraft fees as a measure of liquidity.

[14]Unfortunately, the data do not allow us to determine what cash/check expenses are for. Note that cash/check purchases make up about 20% of overall household spending on average (See Table 1)

The results in this section show that households change their investment and consumption behavior following crypto gains. 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 substantially larger than the MPC out of equity wealth, but smaller than the MPC out of lottery gains. Together, these results suggest that households treat crypto as an asset class that is a hybrid between traditional equity investments and lotteries.

4.1 Crypto Withdrawals Event Study

The consumption changes documented in the previous section occur following largely unrealized crypto gains. As a result, it is not too surprising that the consumption changes are dominated by mostly small changes in discretionary purchases. Spending decisions following large realized gains might follow a different pattern. We explore this aspect by examining household consumption decisions before and after large crypto withdrawals.

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 4 suggest that at least one additional 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 account level. We estimate the following model:

$$y_{i,t} = \beta\, \mathbb{1}(t > \tau_i) + \alpha_i + \gamma_t + \varepsilon_{i,t}, \tag{4}$$

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 $1,000 in our baseline analysis. There are roughly 3,109 such events in our panel data with a median withdrawal size of $2,425. Included in these regressions are account fixed effects (α_i) and year-month fixed effects (γ_t); we also control for average income over the prior 12-months. We restrict the analysis to a window that is 12 months before and after event τ_i. We include all other non-event-window user-months in our sample to more accurately estimate macro trends in consumption through the year-month fixed effects.[15]

The event study establishes a causal relationship in the timing between cryptocurrency withdrawals and consumption changes under the assumption that there are not simultaneous events that drive the timing of both. 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 wealth increase (and a subsequent withdrawal) caused the increase in consumption or the desired increase in consumption caused the drawdown of crypto wealth.

Results in Table 6 report the differences in annualized monthly spending across various cat-

[15]For these observations, which include both non-crypto users and crypto users who are not withdrawing large amounts, the indicator function is always equal to zero.

egories following an individual withdrawing at least $1,000 from a crypto exchange. The coefficient in column (1) indicates that total spending in the year following a large crypto withdrawal increases by $1,451 relative to that household's spending in the prior year and relative to all non-crypto withdrawing households' spending in the same year-month. In contrast to consumption out of crypto gains, there is no statistically significant increase in discretionary spending. Instead, the increased spending is concentrated on housing expenses with large increases in mortgage payments ($479), utilities ($87), and insurance ($80). The only non-housing category that increases post-withdrawal is cash/check, which has a very large ($696), but only marginally significant coefficient. The increases in this category are driven by check spending, and while we can't further identify this spending, it is possible that some of it is also spent on housing if a household pays for the expense (i.e., downpayment or mortgage payment) with a check.

Because large crypto withdrawals are primarily 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 10 where we plot the coefficient in event time relative to the date of a withdrawal from a crypto exchange.[16] The figure shows that spending is constant in the 12-months leading up to a large crypto withdrawal, but mortgage spending rises significantly thereafter. The bottom panel of Figure 10 repeats this analysis for rent. In contrast to mortgage spending, rent spending 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.

We next examine how the effect of crypto withdrawals on mortgage spending varies with the size of the withdrawal. Table 7 reports results for mortgage expenses estimated using the model from Equation 4, but increasing the large withdrawal threshold from $1,000 up to $10,000.

[16] A large withdrawal is defined as ≥$1,000. We include account fixed effects in this regression.

Columns (1) through (3) 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 $1,023 over the next year, more than double the estimated effect from withdrawing at least $1,000.

The evidence suggests that households spend a substantial fraction of large crypto withdrawals on housing, an effect that could be driven by new homeowners or by existing homeowners buying a larger home. In column (4) of Table 7, we re-estimate the event study using an indicator for a new homeowner as the outcome variable. We define a monthly indicator equal to one if a household spends more than $2,500 total on mortgage payments in the forward months 6–12, and spends less than $100 in the prior 6 months.[17] Using this indicator as a proxy for new homeownership, we find that a large crypto withdrawal positively predicts becoming a new homeowner. A large crypto withdrawal increases the probability of transitioning into homeownership by about 1 percentage point, or about 12% relative to the sample mean, although the effect is only marginally significant.

We then estimate the effect of crypto withdrawals on buying a larger home. We define an indicator for upgrading such that for each user-month, an upgrade is equal to one if the difference in total mortgage spending over the next 6 months relative to the prior 6 months is more than $1,000 and the total prior 6 months mortgage spending was greater than $2,500. Based on the large mortgage spending in the prior 6 months, these individuals are existing homeowners that will significantly increase their mortgage payments over the next 6 months, consistent with upgrading their house. Large crypto withdrawals also predict housing upgrades—following a large withdrawal, a household is 1.5 percentage points more likely to buy a larger house, or 7% more likely to upgrade relative to the mean.

[17]We include a 6-month gap after the withdrawal to allow for the timing of the new purchase to not perfectly coincide with the withdrawal.

This evidence demonstrates that household level increases in crypto wealth are being used both to purchase more housing and to purchase a first house. This suggests the possibility that large returns to crypto could have meaningful real effects on the prices of local housing markets. We examine this aspect in the next section.

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 5 shows that household crypto wealth is geographically concentrated. In this section, we explore the extent to which aggregate changes in crypto wealth affect local housing markets. We first define monthly county-level crypto wealth as

$$\text{CryptoWealth}_{c,t} = \sum_{i \in c} \text{CryptoWealth}_{i,t} \tag{5}$$

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

$$\text{CryptoGains}_{c,t} = \frac{\text{CryptoWealth}_{c,t} - \text{CryptoWealth}_{c,t-12} + \text{NetCryptoWithdrawals}_{c,t-12\rightarrow t}}{\text{Households}_{c,y-1}}. \tag{6}$$

$\text{NetCryptoWithdrawals}_{c,t-12\rightarrow t}$ 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 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 crypto gains, which allows us to compare across counties despite variation in housing market size. We create these measures based on the entire database of user transactions, but filtering the transactions to users that are flagged by the data provider as high quality. This results in aggregating county-level crypto transactions based on approximately a 10% sample of users, or roughly 6 million households.

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

$$\log ZHVI_{c,t} = \beta_{OLS} \log \text{CryptoGains}_{c,t} + \phi_s \log ZHVI_{c,t-1} + \alpha_c + \alpha_t + \varepsilon_{c,t}, \tag{7}$$

where $ZHVI_{c,t}$ 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.

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 7 potentially suffers from reverse causality—increasing house prices in an area might cause households to sell cryptocurrency to fund a house purchase, which simultaneously reduces the value of the county crypto portfolio. To the extent reverse causality exists in the data, the OLS estimate will be biased downward. 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 exposure to crypto 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. Given the massive returns over this period, early investors in Bitcoin experienced a substantial increase in crypto wealth, while later adopters missed out on much or all of this wealth accumulation. The run-up in Bitcoin prices led to large withdrawals from crypto exchanges, and our evidence in Section 4.1 shows that large withdrawals are 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 exposure before the price run-up to counties with low-levels of crypto exposure. Formally, we estimate

$$\log\ ZHVI_{c,t} = \beta\, \text{HighCrypto}_{c,2016} \times \text{Post}_t + \phi_s \log\ ZHVI_{c,t-1} + \alpha_c + \alpha_t + \varepsilon_{c,t}, \tag{8}$$

where $\text{HighCrypto}_{c,2016}$ is an indicator variable 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. The top panel of Figure 11 shows the geographic dispersion of high vs. low crypto exposure counties in our sample. Post_t is an indicator variable equal to one for months after the run-up induced crypto withdrawals began. We define event-month zero of the post-period as October 2017, which is the month preceding the beginning of a jump in crypto withdrawals. The bottom panel of Figure 11 shows that high exposure counties have a much larger spike in crypto withdrawals during this post-period than low exposure counties.[18] This is the primary treatment through which we will identify the effect of crypto gains on house prices. We limit our sample to the 6 months before and after this post-period begins. The coefficient on the interaction term, β, estimates the differential effect of this crypto wealth shock on county house prices.

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 exposure counties would have evolved similarly. While this assumption is not testable, we shed light on its plausibility by examining trends in house prices across high and low exposure counties prior to the Bitcoin run-up. To get a preliminary sense of these trends, the top panel of Figure 12 plots the average ZHVI price index separately for high and low exposure counties, after normalizing the indices to one in December 2016. The vertical line is drawn at the month before the post-period begins. The data clearly suggest that house prices followed similar trends in the high and low exposure counties before the crypto wealth shock. Post-shock, house prices are higher in high crypto exposure counties.

To more rigorously examine these trends, in the bottom panel of Figure 12 we plot the coefficients obtained from estimating a version of Equation 8 that interacts the high crypto exposure indicator with indicators for each month in the 12-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, consistent with the parallel trend assumption. Together, the evidence in Figure 12 suggests that house prices would likely have continued to follow similar trends in high and low crypto exposure counties absent any

[18] We draw the vertical line in the figure at event-month $t = -1$.

crypto wealth shock. 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 that differentially affects house prices in high and low crypto exposure counties. Given the volatility of Bitcoin, both the timing and magnitude of the run-up can reasonably be thought of as random. However, county exposure to crypto is not random. Because we focus on historical county crypto exposure, 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 exposure is correlated with other time-varying county characteristics that confound the interpretation of our experiment. The geographic dispersion of high vs. low crypto exposure counties in our sample visible in the top panel of Figure 11 suggests one possible concern. While there is substantial variation in crypto exposure in the interior of the country, most of both coasts are made up of high crypto exposure counties. These areas are more wealthy and also have higher levels of equity market exposure.[19] 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 (top vs. bottom panel of Figure A.1).[20] 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 do not spike around the crypto wealth shock. Instead, Nasdaq returns are relatively flat or even falling

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

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

in the months around the large spike in Bitcoin returns. Second, while high exposure counties have a large spike in crypto withdrawals following the Bitcoin run-up, Figure A.2 shows no discontinuous change in withdrawals from brokerage accounts around this event, suggesting that high crypto exposure counties are not realizing especially large equity gains in the post-period. Finally, our difference-in-difference results are also robust to controlling for county-level exposure to equity interacted with the post indicator. Together, these results suggest that it is unlikely that our results are driven by an equity market shock.

We estimate the difference-in-differences specification in Equation 8 and report the results in Table 8. We estimate both the traditional difference-in-differences coefficient using an indicator for high crypto wealth counties (columns (1) and (3)), as well as a continuous version where we interact the post indicator with the log county crypto wealth per capita as of 2016 (columns (2) and (4)).[21] Across both specifications, we show that counties with high crypto exposure experience higher house prices in the months after the Bitcoin price run-up relative to low crypto exposure counties. In columns (1) and (2), we report the estimates without any fixed effects. The estimated effect of crypto wealth on county house prices in column (1) indicates that house prices grow about 3 basis points faster in the post-period in high crypto exposure counties relative to low exposure counties, or roughly 8% of the standard deviation in house price growth over 2018. The continuous specification implies a similar economic magnitude. The estimated elasticity combined with a change in county crypto wealth from the 50^{th} to the 75^{th} percentile indicates that house prices increase by about 1.4 basis points.[22] The estimates are nearly identical, both in magnitude and statistical significance, after adding county and month fixed effects (see columns (3) and (4)).

[21]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.

[22]The 50^{th} percentile is 0.706 and the 75^{th} percentile is 2.396, so the elasticity implies an increase of $(\frac{2.396}{0.706})^{0.000114}$.

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 that isolates variation in crypto gains that comes solely from the returns to cross-sectional historical differences in crypto holdings.

We construct an instrument for $\text{CryptoGains}_{c,t}$ using the 12-month Bitcoin net return over the year multiplied by the county's crypto wealth 12-months earlier,

$$\text{PassiveGains}_{c,t} = \frac{\text{CryptoWealth}_{c,t-12}}{\text{Households}_{c,y-1}} \times \left[\frac{BTC_t}{BTC_{t-12}} - 1\right], \tag{9}$$

where BTC_t is the price of Bitcoin in month t. This instrument can be interpreted as the change in county crypto assets per capita over the prior 12-months caused solely by the performance of that county's initial allocation to crypto. As discussed above, the naïve estimate of the effect of crypto wealth on county house prices suffers from two biases: reverse causality and potential changes in non-crypto county wealth simultaneously causing higher house prices and more investment in crypto. The 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 anything additional over the year. This excludes any variation in the change in the county-level crypto holdings that comes from the potentially endogenous decision to deposit or withdraw crypto over that period.[23]

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 returns over the prior year and heterogeneity in lagged crypto

[23]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.7.

exposure) 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 returns are correlated with equity returns and that county-level heterogeneity in crypto exposure is also correlated with heterogeneity in equity exposure. To alleviate this concern, we construct an alternative instrument that represents the excess Bitcoin return over equity market returns during the contemporaneous period.

$$\text{ExcessPassiveGains}_{c,t} = \frac{\text{CryptoWealth}_{c,t-12}}{\text{Households}_{c,y-1}} \times \left[\frac{BTC_t}{BTC_{t-12}} - \frac{Nasdaq_t}{Nasdaq_{t-12}} \right], \tag{10}$$

Under this definition, our instrument represents the passive excess return of Bitcoin relative to the return on Nasdaq. This modification results in 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 strikingly similar results, suggesting that equity returns do not drive our results. Consequently, we believe that these passive crypto gains are plausibly exogenous to county house prices.

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

$$\text{CryptoGains}_{c,t} = \beta_{FS}\,\text{Instrument}_{c,t} + \phi_s \Delta\, ZHVI_{c,t-3\to t} + \alpha_c + \alpha_t + \xi_{c,t}. \tag{11}$$

Unsurprisingly, the returns to initial crypto holdings strongly predict county-level crypto gains—the first stage F-statistic ranges from 2,000 to 7,000 across our main specifications. We then use the predicted crypto gains from Equation 11 to estimate the following second stage regression:

$$\Delta ZHVI_{c,t\to t+6} = \beta_{IV}\, \widehat{\text{CryptoGains}}_{c,t} + \phi_s \Delta ZHVI_{c,t-3\to t} + \alpha_c + \alpha_t + \zeta_{c,t}, \tag{12}$$

where we measure changes in the housing price index, $ZHVI_{c,t}$ over the six months following the current month. We also examine changes over the following 12 months. Table 9 reports the results from estimating the 2SLS specification in Equation 12.[24] We find that growth in county crypto wealth causes county house prices to go up over the next 6 months, and to rise even more over the following 12 months. The estimates are highly statistically significant, robust to including fixed effects, and similar using either the *PassiveGains* or *ExcessPassiveGains* instruments.

Looking across Table 9, the estimates indicate that \$1 of crypto wealth gains per person in a county drive house prices up by about \$0.18 over the next six months, or about \$0.40 over the following year. These estimates imply that a one standard deviation increase in county per capita crypto gains leads to a \$215 dollar increase in county house prices over the next year. This is about a 7 basis point increase in prices relative to the sample median, which is a roughly similar magnitude to the estimates obtained in the difference in differences analysis.

Together, the evidence in this section and in section 5.1 show that crypto wealth has a spillover effect on the real economy. Counties that are highly exposed to crypto assets experience faster house price growth following large crypto returns.

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

[24]We report OLS, first stage, and reduced form results in Appendix Table A.6.

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.

References

Agarwal, Sumit, and Wenlan Qian, 2014, Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in singapore, *American Economic Review* 104, 4205–30.

Aiello, Darren, Scott R. Baker, Tetyana Balyuk, Marco Di Maggio, Mark J. Johnson, Jason Kotter, and Emily Williams, 2023, Cryptocurrency investing: Stimulus checks and inflation expectations, Working Paper.

Aladangady, Aditya, 2017, Housing wealth and consumption: Evidence from geographically-linked microdata, *American Economic Review* 107, 3415–46.

Baker, Malcolm, Stefan Nagel, Jeffrey Wurgler, et al., 2007, The effect of dividends on consumption, *Brookings Papers on Economic Activity* 38, 231–292.

Baker, Scott R, 2018, Debt and the response to household income shocks: Validation and application of linked financial account data, *Journal of Political Economy* 126, 1504–1557.

Baker, Scott R, Robert A Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis, 2020, How does household spending respond to an epidemic? consumption during the 2020 covid-19 pandemic, *The Review of Asset Pricing Studies* 10, 834–862.

Baker, Scott R., and Lorenz Kueng, 2022, Household financial transaction data, *Annual Review of Economics* 14, 47–67.

Balyuk, Tetyana, and Emily Williams, 2021, Friends and family money: P2p transfers and financially fragile consumers, *Available at SSRN* .

Benetton, Matteo, and Giovanni Compiani, 2022, Investors' beliefs and cryptocurrency prices, *Working Paper* .

Berger, David, Veronica Guerrieri, Guido Lorenzoni, and Joseph Vavra, 2018, House prices and consumer spending, *The Review of Economic Studies* 85, 1502–1542.

Carroll, Christopher, Misuzu Otsuka, and Jiri Slacalek, 2011, How large are housing and financial wealth effects? a new approach, *Journal of Money, Credit, and Banking* 43, 55–79.

Case, Karl E, John M Quigley, and Robert J Shiller, 2005, Comparing wealth effects: the stock market versus the housing market, *Advances in macroeconomics* 5.

Chava, Sudheer, Fred Hu, and Nikhil Paradkar, 2022, Gambling on crypto tokens?, *Available at SSRN 4149937* .

Chodorow-Reich, Gabriel, Plamen T Nenov, and Alp Simsek, 2021, Stock market wealth and the real economy: A local labor market approach, *American Economic Review* 111, 1613–57.

Di Maggio, Marco, Amir Kermani, and Kaveh Majlesi, 2020, Stock market returns and consumption, *The Journal of Finance* 75, 3175–3219.

Di Maggio, Marco, Emily Williams, and Justin Katz, 2022, Buy now, pay later credit: User characteristics and effects on spending patterns, Technical report, National Bureau of Economic Research.

Divakaruni, Anantha, Peter Zimmerman, et al., 2021, Uncovering retail trading in bitcoin: The impact of covid-19 stimulus checks, Technical report, Federal Reserve Bank of Cleveland.

Fagereng, Andreas, Martin B Holm, and Gisle J Natvik, 2021, Mpc heterogeneity and household balance sheets, *American Economic Journal: Macroeconomics* 13, 1–54.

Hackethal, Andreas, Tobin Hanspal, Dominique M Lammer, and Kevin Rink, 2022, The characteristics and portfolio behavior of bitcoin investors: Evidence from indirect cryptocurrency investments, *Review of Finance* 26, 855–898.

Hartman-Glaser, Barney, Mark Thibodeau, and Jiro Yoshida, 2018, Cash to spend: Ipo wealth and house prices, *Available at SSRN 3329651* .

Hartzmark, Samuel M, and David H Solomon, 2019, The dividend disconnect, *The Journal of Finance* 74, 2153–2199.

Jappelli, Tullio, and Luigi Pistaferri, 2014, Fiscal policy and mpc heterogeneity, *American Economic Journal: Macroeconomics* 6, 107–36.

Johnson, David S., Jonathan A. Parker, and Nicholas S. Souleles, 2006, Household expenditure and the income tax rebates of 2001, *American Economic Review* 96, 1589––1610.

Kaplan, Greg, and Giovanni L. Violante, 2014, A tale of two stimulus payments: 2001 vs. 2008, *American Economic Review: Papers and Proceedings* 104, 3415–46.

Kogan, Shimon, Igor Makarov, Marina Niessner, and Antoinette Schoar, 2022, Are cryptos different? evidence from retail trading, *SSRN Working Paper 4289513* .

Makarov, Igor, and Antoinette Schoar, 2021, Blockchain analysis of the bitcoin market, *NBER Working Paper 29396* .

Wheat, George Eckerd, Chris, 2022, The dynamics and demographics of u.s. household crypto-asset use, *Working Paper* .

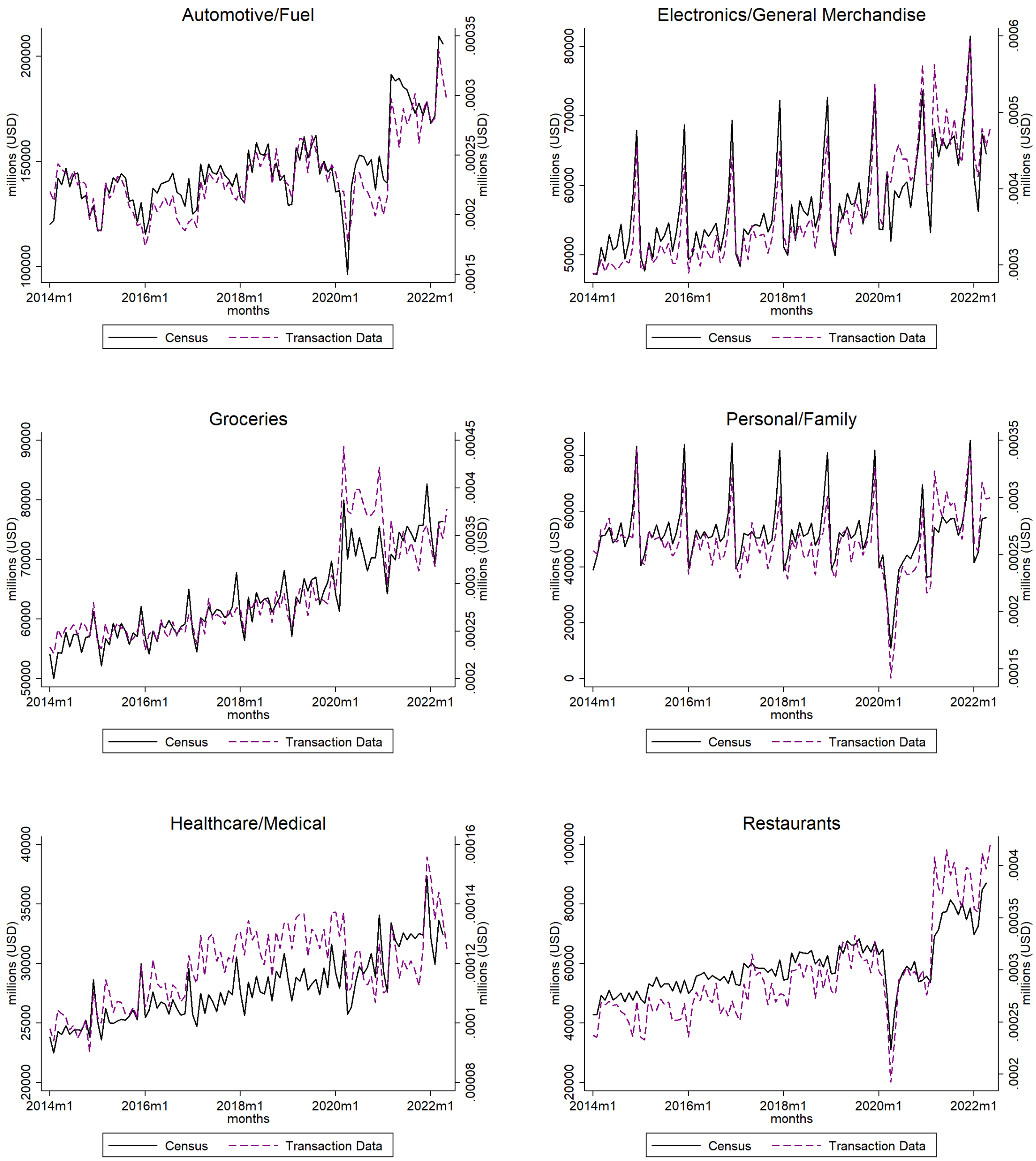


Figure 1. Spending in Data vs. Census Retail Sales. Each panel displays two monthly series from January 2014–July 2022. The solid line displays total sales in the specified category from the Census Retail Sales. The dotted line displays spending per user in the specified category as observed in the data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

mem_id	bank_id	amount	description	date	type
5.975e+23	5.578e+23	100	DEBIT CARD PURCHASE XXXXX4106 COINBASE SAN FRANCIS CA	2021-01-28	debit
1.161e+24	8.362e+23	50	COINBASE.COM XXXXXXXXXX ***********9565~~XXXXX~~~~XXXXX~~0~~~~0065	2021-01-25	debit
1.161e+24	8.362e+23	100	COINBASE.COM XXXXXXXXXX ***********9565~~XXXXX~~~~XXXXX~~0~~~~0065	2021-01-25	debit
1.161e+24	8.362e+23	1000	COINBASE.COM XXXXXXXXXX ***********9565~~XXXXX~~~~XXXXX~~0~~~~0065	2021-01-25	debit
4.985e+23	9.281e+23	100	PRM*8700 BINANCE.US 702-XXXXXXX NV~~XXXXX~~XXXXXX******0161~~XXXXX~~0~~~~0079	2021-01-20	debit
4.985e+23	9.281e+23	100	PRM*8700 BINANCE.US 702-XXXXXXX NV~~XXXXX~~XXXXXX******0161~~XXXXX~~0~~~~0079	2021-01-25	debit
4.985e+23	9.281e+23	50	PRM*8700 BINANCE.US 702-XXXXXXX NV~~XXXXX~~XXXXXX******0161~~XXXXX~~0~~~~0079	2021-01-29	debit
3.092e+23	3.867e+23	1000	COINBASE.COM XXXXXXXXXX 55	2021-01-11	debit
3.092e+23	3.867e+23	.11	COINBASE.COM XXXXXXXXXX	2021-01-08	credit
1.132e+24	4.193e+23	5000	ACH ELECTRONIC DEBIT GEMINI TRUST CO ACH TXFER CXXXXXXX	2021-01-13	debit
4.672e+23	7.094e+23	1970.2	COINBASE.COM DES:XXXXXXXXXX ID: INDN:XXXX X XXXXXXX CO ID:1455	2021-01-07	credit
5.975e+23	5.578e+23	181	DEBIT CARD PURCHASE XXXXX4106 COINBASE SAN FRANCIS CA	2021-01-25	debit
5.975e+23	5.578e+23	200	DEBIT CARD PURCHASE XXXXX4106 COINBASE SAN FRANCIS CA	2021-01-25	debit
5.224e+23	5.082e+23	230	XXXXXXXXXX COINBASE.COM E50F XXXXXXX X XXXX ACH CREDIT	2021-01-11	credit
4.985e+23	9.281e+23	100	COINBASE SAN FRANCISCOCA~~XXXXX~~XXXXXX******0161~~XXXXX~~0~~~~0079	2021-01-11	debit
7.042e+23	9.848e+23	200	COINBASE INC. XXXXXXXXXX ***********WPDD~~XXXXX~~~~XXXXX~~0~~~~0065	2021-01-12	debit

Figure 2. Examples of Crypto Exchange Transactions. This figure displays a sample of user transactions with cryptocurrency exchanges, including both deposits and withdrawals.

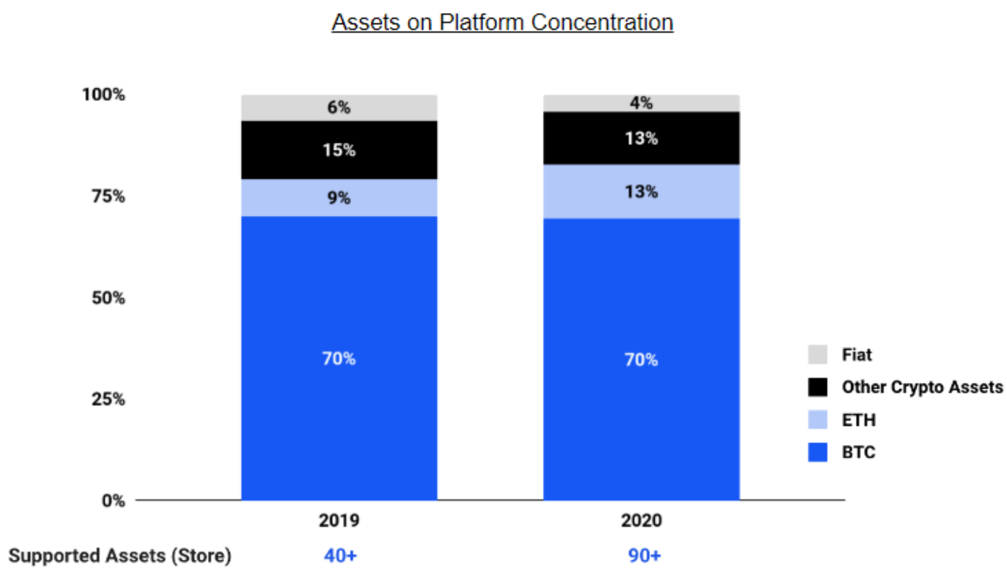


Figure 3. Cryptocurrency Assets Held Through Coinbase. This figure shows the percentage of various cryptocurrencies held on Coinbase in 2019 and 2020. Source: Coinbase S-1 filed on March 23, 2021.

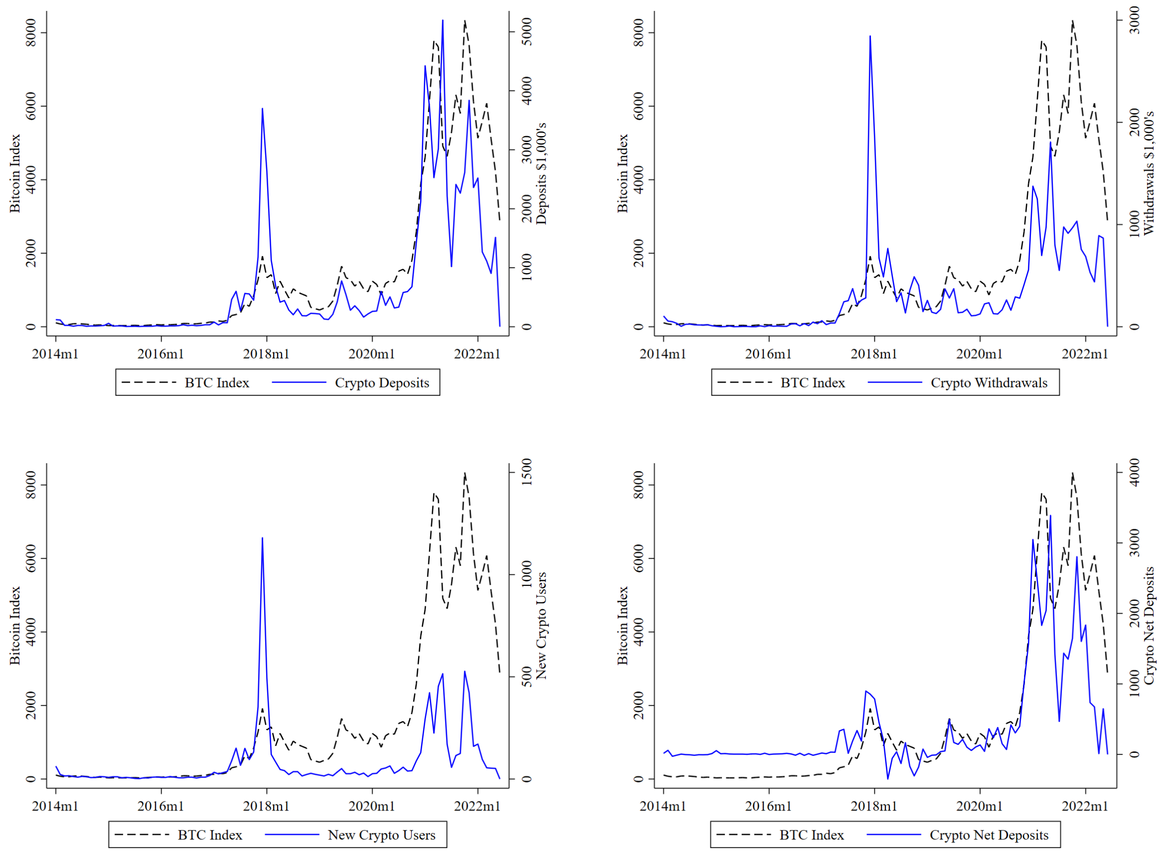


Figure 4. Crypto Adoption and Crypto Portfolio Activity. This figure shows the relation between retail crypto activity and Bitcoin prices. Panel (a) depicts flows of deposits into cryptocurrencies. Panel (b) shows withdrawals or redemption of crypto. Panel (c) shows the number of new crypto users in the month, where a new user is defined by the first deposit into crypto greater than $5. Finally, Panel (d) shows the net deposits into crypto which is the total deposits minus withdrawals.

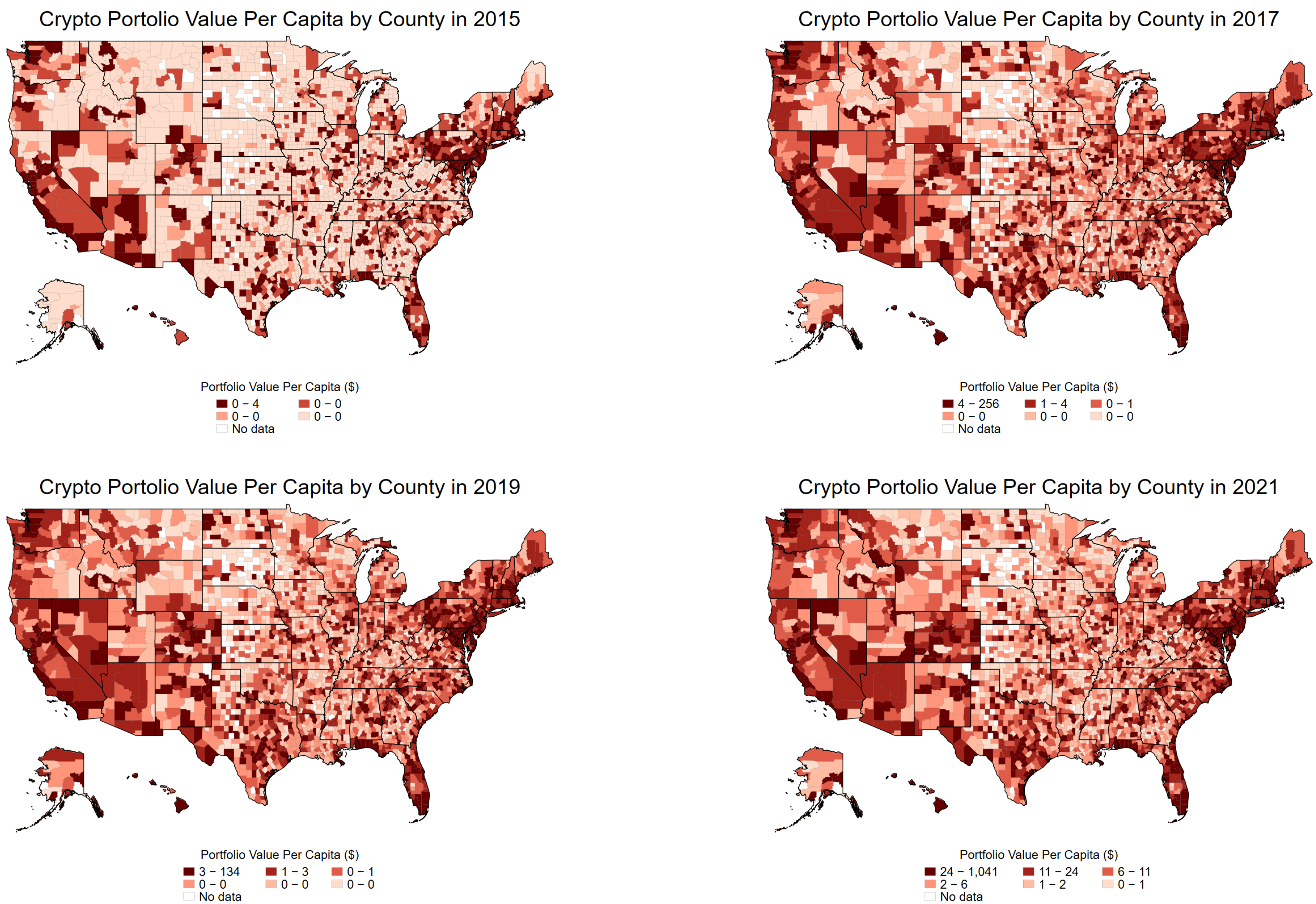


Figure 5. Crypto User Geography over Time. This figure shows the geographic evolution of crypto activity over time. We identify transactions to cryptocurrency exchanges and assume that deposits and withdrawals represent either buying or selling Bitcoin at that day's price. We then aggregate these transactions to calculate the total crypto portfolio value at the county-level. The four panels show snapshots of county-level crypto portfolio values divided by county population in December 2015, 2017, 2019, and 2021.

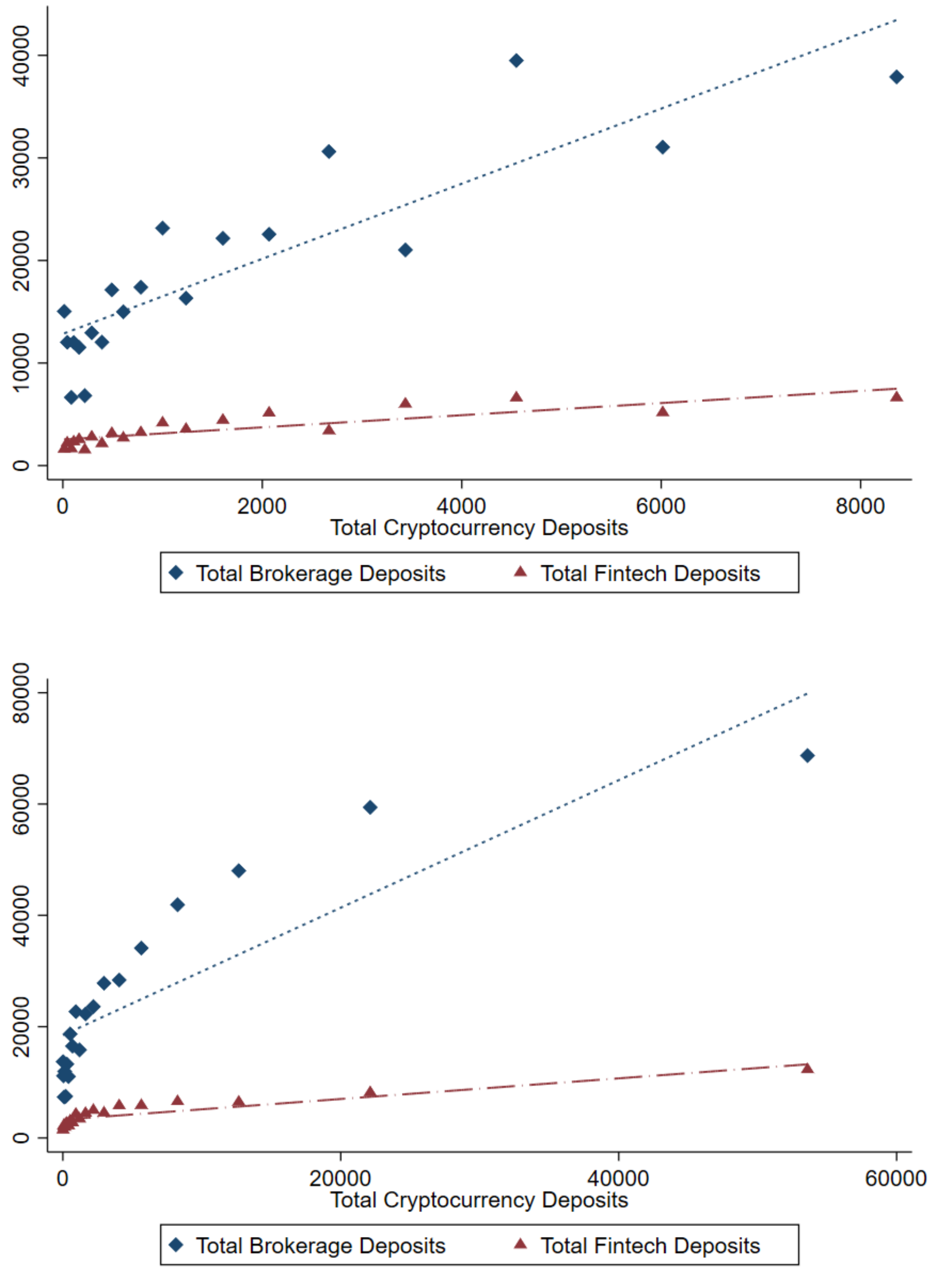


Figure 6. Cryptocurrency Deposits and Equity Investments. Each panel depicts a cross-sectional bin-scatter plot of total deposits to brokerages and to FinTech brokerages against total cryptocurrency exchange deposits. Underlying data are at a user level. FinTech exchanges are defined as deposits to Robinhood, Stash, and Acorns. Top panel is censored, displaying only users with less than $10,000 in total cryptocurrency exchange deposits.

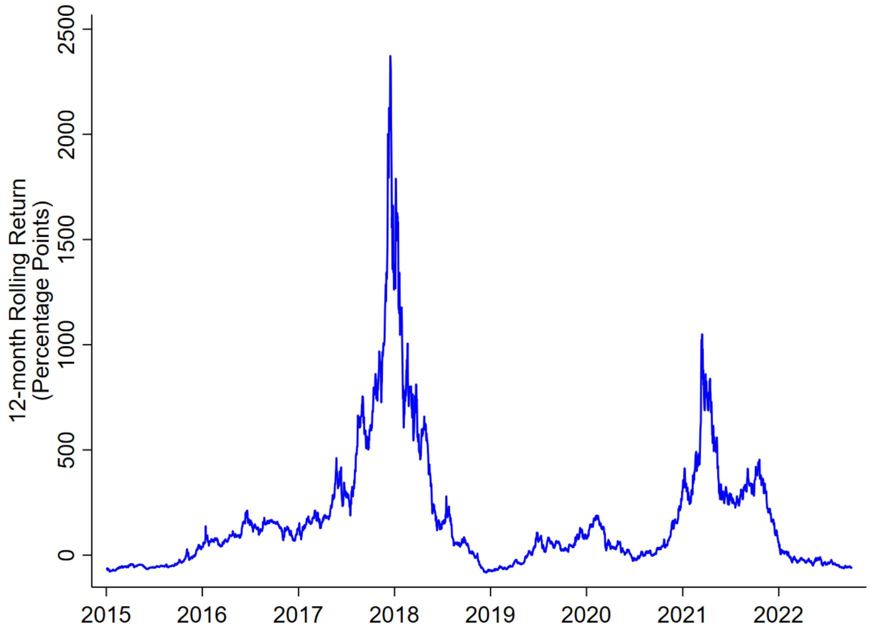


Figure 7. Bitcoin Rolling 12-month Returns. This figures plots the daily 12-month rolling Bitcoin returns. Source: *Wall Street Journal* (WSJ).

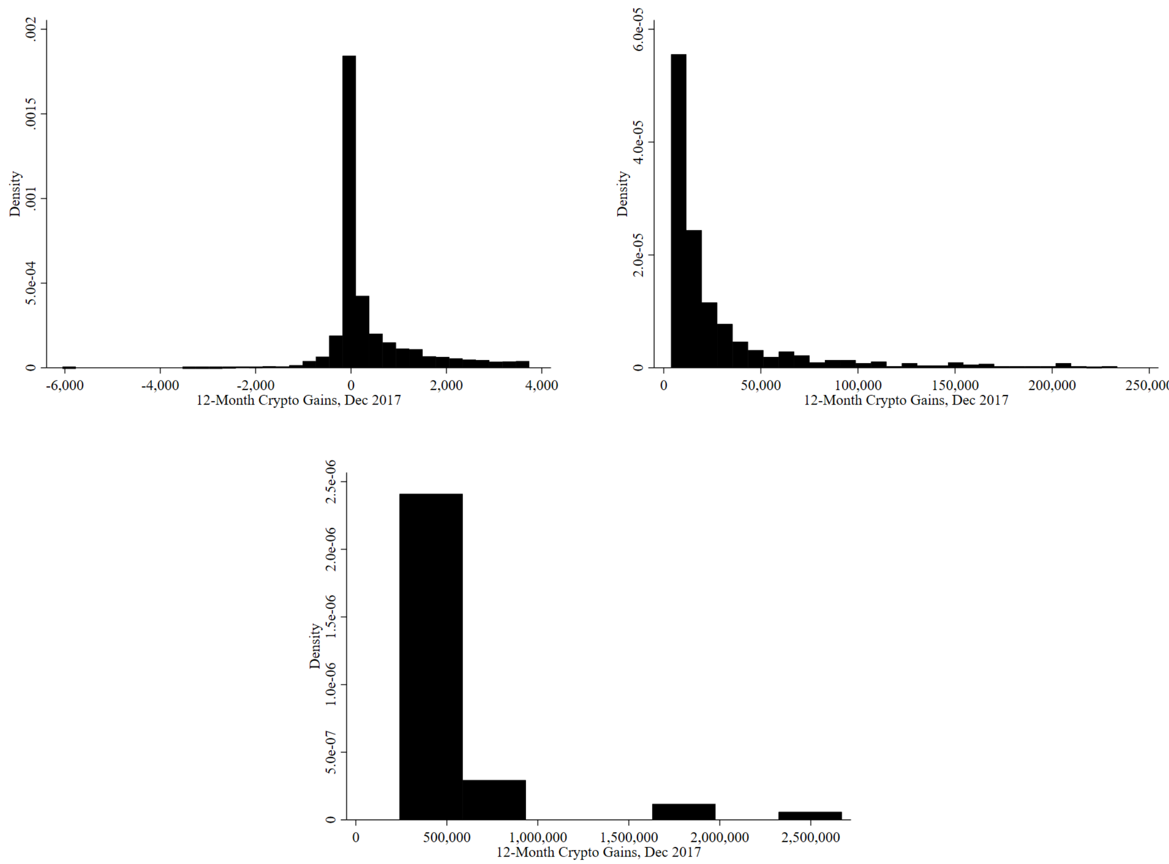
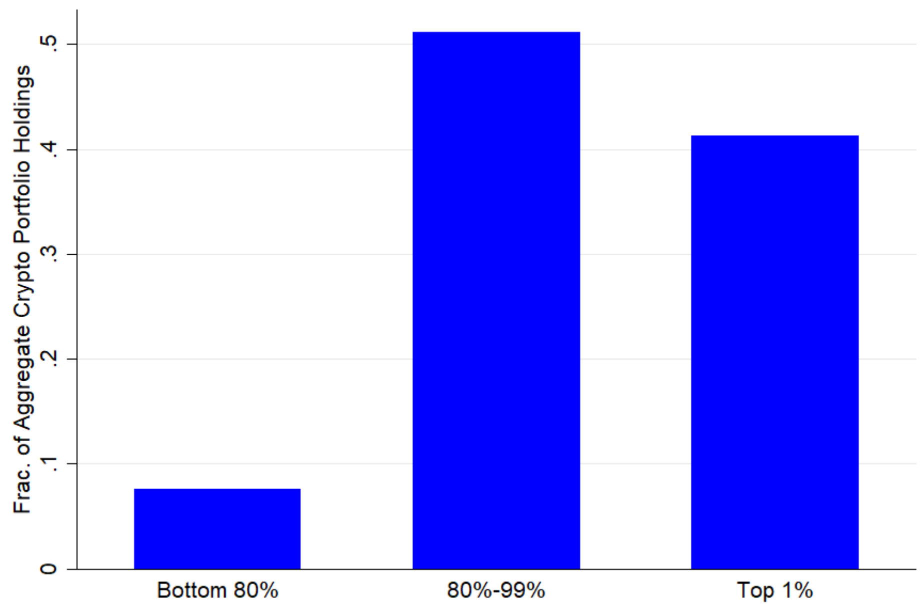


Figure 8. Distribution of 12-month Crypto Gains in December 2017. This figure shows the distribution of gains over the prior 12 months at the end of 2017. The distribution is divided into three groups. Panel (a) shows the gains in the bottom 80th percentile. Panel (b) shows the 80th percentile to the 99th percentile. Panel (c) shows those greater than the 99th percentile.



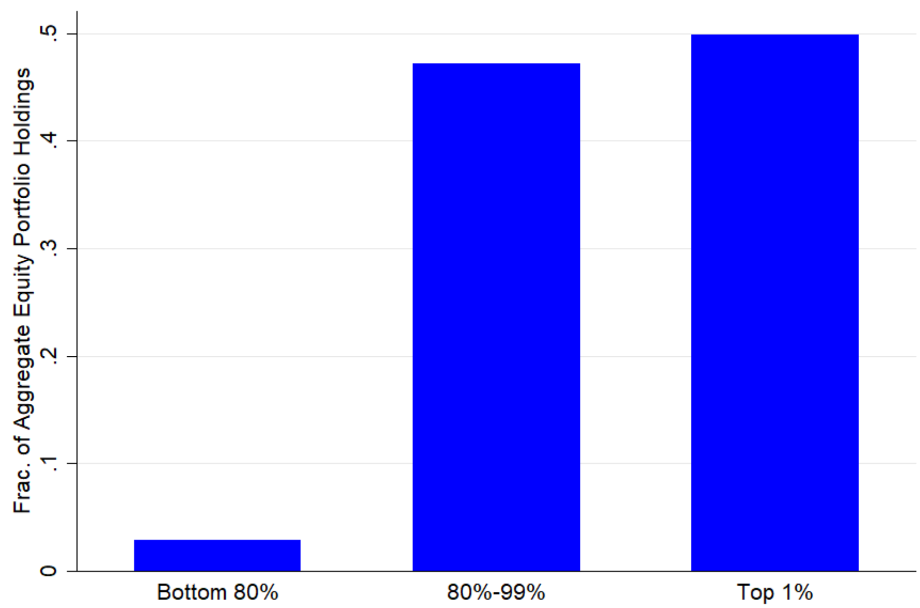


Figure 9. Distribution of Investment Wealth. These figure show the distribution of investment wealth. The top figure presents the distribution of total crypto portfolio values as of December 2017 for our sample. The bottom figure shows the distribution of equity portfolio values based on the Survey of Consumer Finances (SCF).

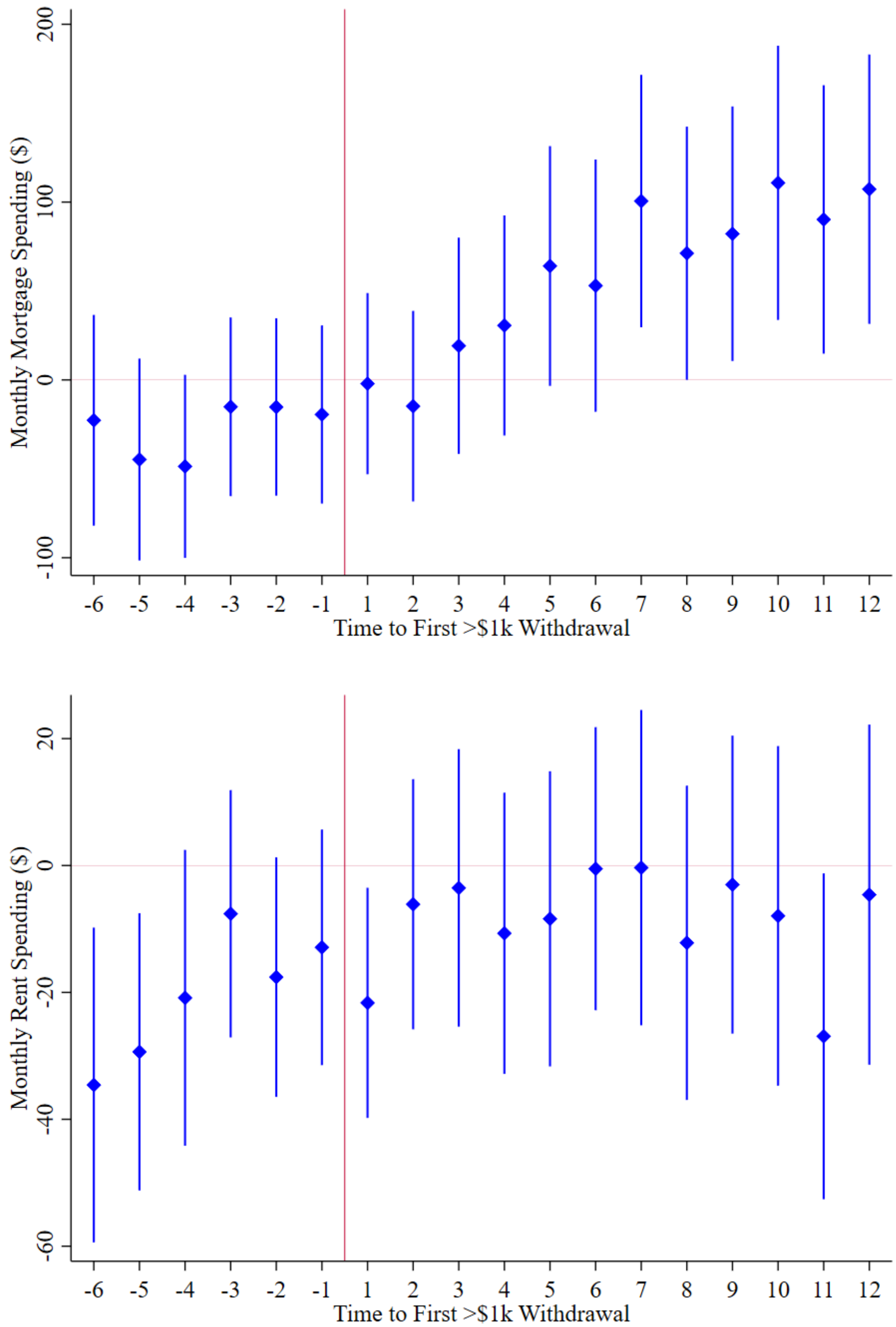


Figure 10. Monthly Mortgage and Rent Spending Around First Large Bitcoin Withdrawal. Each panel plots the coefficients on an event-study regression for the months before and after a user first withdraws at least $1,000 from a cryptocurrency exchange. The top panel shows monthly mortgage spending around this event, while the bottom panel shows spending on monthly rent.

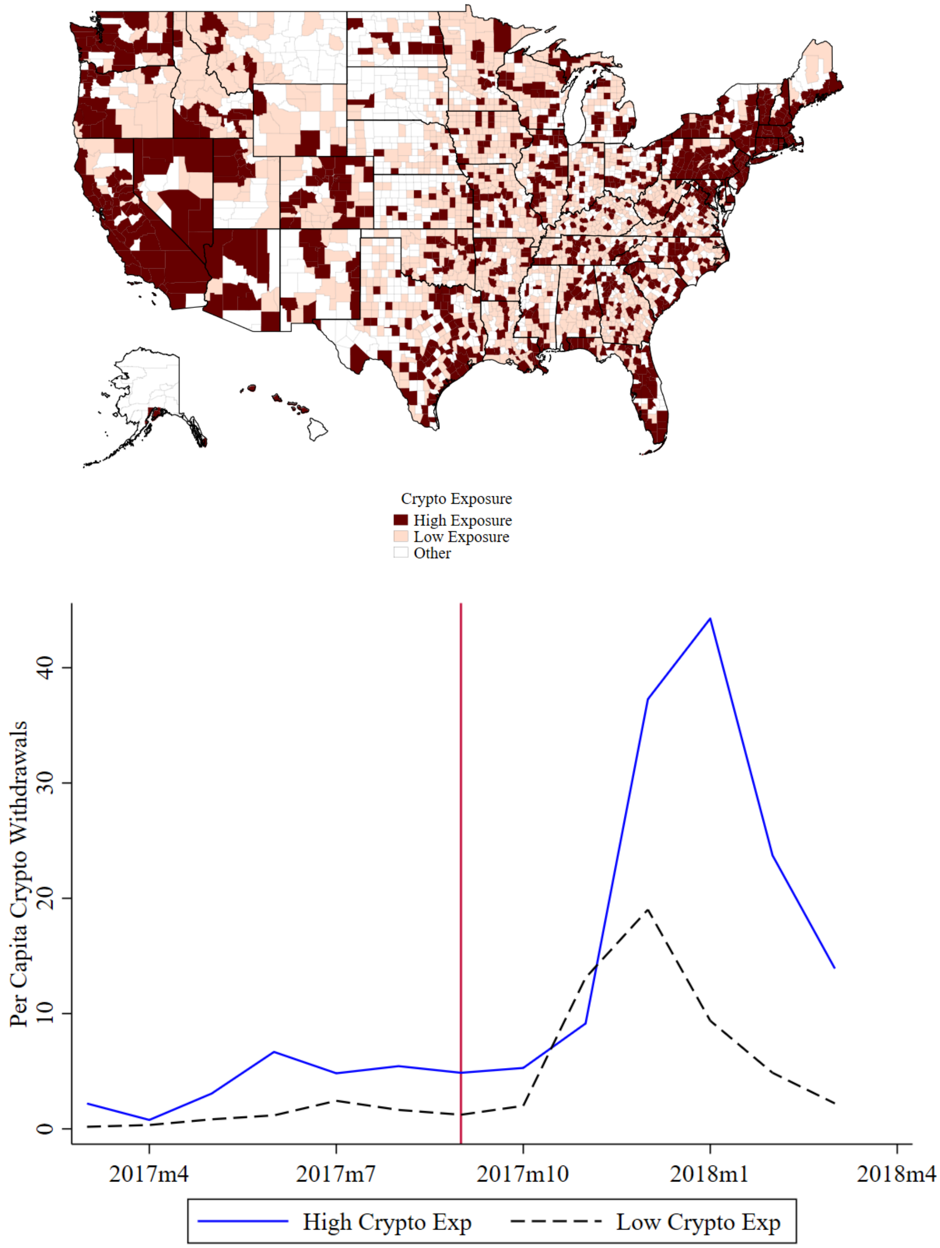
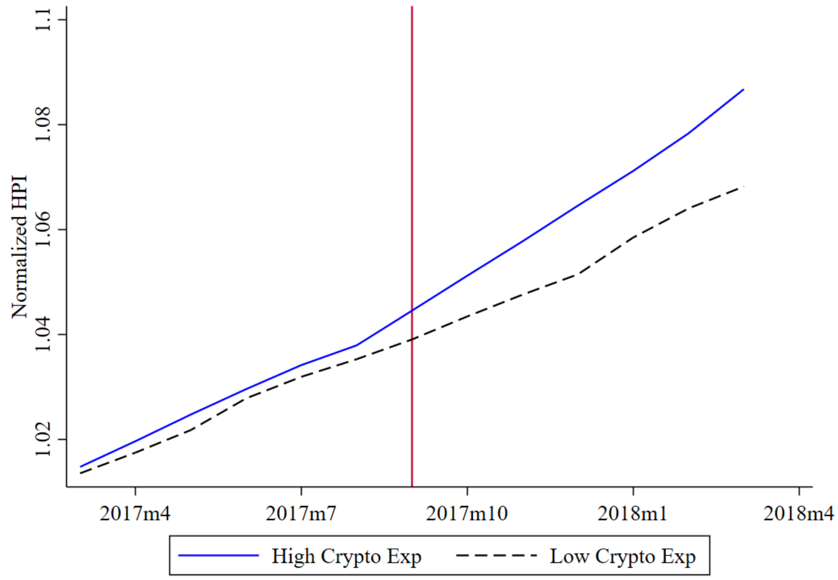


Figure 11. Crypto County Exposure and Withdrawals during the Bitcoin Run-up. The map in the top panel highlights counties that have per capita crypto holdings in the top tercile as of December 2016 (dark red); these are the treated counties in our difference-in-difference analysis. The bottom panel shows the average per capita withdrawals separately for counties with high and low crypto exposure (top and bottom terciles). The vertical line separates the sample into pre- and post-Bitcoin run-up in 2017; the line is drawn at month *t*=-1 in event time, which we define as the month before county-level crypto withdrawals began to spike.



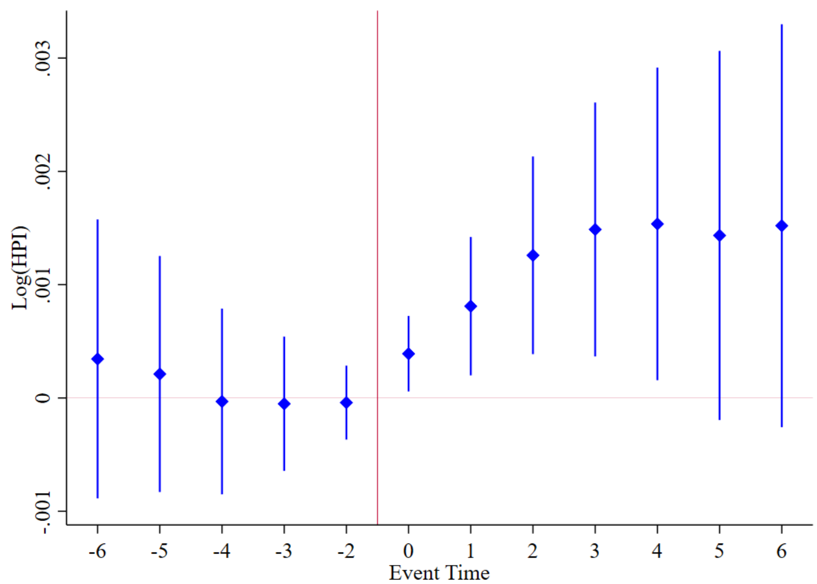


Figure 12. The Bitcoin Run-Up Diff-In-Diff. This figure shows our difference-in-differences analysis of the aggregate effect of county-level crypto exposure on county-level house prices. Treated (control) counties are defined as counties that are in the top (bottom) tercile of crypto holdings per capita as of December 2016 (see Figure 11). The treatment is defined as the unusually large run-up in Bitcoin prices in late 2017; the vertical line is drawn at the month preceding the large spike in crypto withdrawals seen in Figure 11 (i.e., month t=-1 in event time). We set event-month t=-1 to be the baseline (omitted) in Panel (b). The top panel shows the evolution of raw house prices across treated and control counties; we normalize price indices as of December 2016. The bottom panel shows estimates of the monthly difference in log house prices between treated and control counties.

Table 1

Summary Statistics of Sample and Crypto Users

This table shows sample means and standard deviations [in brackets]. Data are based on a user-level panel of monthly transaction data. The sample includes 100,652 users, of whom 1,370 have crypto transactions before July 2017 (early adopters), and 3,517 have crypto transactions between July and December 2018 (late adopters).

Variable	Early Adopter	Late Adopter	Never Adopter
Total Income	8,747	8,135	7,212
	[9,630]	[8,981]	[7,910]
Total Spending	7,247	6,578	6,160
	[7,913]	[6,835]	[6,458]
Traditional Investment	321	257	120
	[2,578]	[2,223]	[1,635]
FinTech Investment	49	56	7
	[910]	[1,211]	[382]
Crypto Investment	168	96	0
	[1,937]	[1,898]	[0]
Percent of Spending:			
Auto/Fuel	5.0	5.3	4.9
	[8.4]	[10.4]	[14.3]
Cable/Telecom	5.3	5.5	6.0
	[26.9]	[29.6]	[52.8]
Cash/Check	20.7	19.7	22.0
	[27.3]	[123.2]	[58.3]
Charity	0.4	0.4	0.5
	[11.8]	[3.6]	[27.5]
Education	0.4	0.2	0.1
	[34.8]	[240.3]	[747.2]
Entertainment/Travel	8.1	7.8	6.3
	[12.9]	[25.1]	[118.4]
Gen. Merch.	19.8	20.8	21.3
	[48.9]	[65.3]	[421.1]
Groceries	8.4	8.4	9.0
	[10.1]	[43.0]	[72.6]
Insurance	4.5	4.6	4.8
	[28.1]	[22.9]	[41.6]
Medical	1.9	1.9	2.1
	[4.6]	[5.8]	[26.4]
Mortgage	9.7	9.6	9.1
	[19.6]	[18.5]	[66.5]
Rent	2.2	2.3	1.6
	[12.7]	[9.9]	[16.1]
Restaurants	9.7	10.0	8.6
	[11.9]	[14.8]	[79.8]
Utilities	3.9	3.7	3.8
	[8.0]	[7.9]	[14.9]

Table 2

Crypto Gains and Investment

This table tests the sensitivity of crypto and equity investments to gains in crypto wealth following the run-up in Bitcoin prices in 2017. The primary independent variable is the gain crypto wealth from year end 2016 to 2017. The dependent variable in Panel A is the sum of crypto deposits in 2018. In Panel B the dependent variable is the sum of deposits made in traditional equity investments in 2018. Finally, in Panel C the dependent variable is the sum of crypto withdrawals in 2018. Included as a control is the individual's average monthly income in 2018 and either the sum of crypto deposits in 2017 (Panels A and C) or the sum of investment deposits in 2017 (Panel B). Column (1) in each panel uses the entire sample of users. Columns (2)–(4) use subsamples that include non-crypto users and crypto users with gains below the 80^{th} percentile, 80^{th} to 99^{th}, and above 99^{th}, respectively. t-statistics in parentheses are heteroskedasticity-robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Crypto Deposits

	12-Month post-Peak Gross Crypto Deposits			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
12-Month Crypto Gains, December 2017	0.00623***	0.0482	0.0826***	0.0138**
	(12.34)	(0.34)	(5.23)	(2.06)
Crypto Deposits 2017	0.00216***	0.00433***	0.00389***	0.00565*
	(9.46)	(3.89)	(3.58)	(1.87)
Average Monthly Income, 2018	0.00160***	0.00658***	0.00482***	0.00413***
	(6.84)	(3.61)	(3.02)	(3.09)
Sample	All Gains	<80 ptile Gains	[80,99) ptile Gains	>99 ptile Gains
Observations	100,652	99,676	96,701	95,823
Adj. R^2	0.042	0.002	0.067	0.037

Panel B: Investment Deposits

	12-Month post-Peak Investment Deposits			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
12-Month Crypto Gains, December 2017	0.0104**	-0.0154	0.0202***	0.00181
	(2.12)	(-0.10)	(2.85)	(0.51)
Investment Deposits 2017	0.720***	0.733***	0.722***	0.722***
	(77.27)	(29.37)	(29.14)	(28.20)
Average Monthly Income, 2018	0.107***	0.140***	0.138***	0.138***
	(16.91)	(11.27)	(11.03)	(10.96)
Sample	All Gains	<80 ptile Gains	[80,99) ptile Gains	>99 ptile Gains
Observations	100,652	99,676	96,701	95,823
Adj. R^2	0.399	0.427	0.418	0.418

Table 2: Continued

Panel C: Crypto Withdrawals

	12-Month post-Peak Gross Crypto Withdrawals			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
12-Month Crypto Gains, December 2017	0.0312***	0.0666	0.0964***	-0.0119
	(7.66)	(0.52)	(3.00)	(-1.52)
Crypto Deposits 2017	0.0249***	0.00889*	0.0589*	-0.156
	(3.04)	(1.85)	(1.89)	(-1.65)
Average Monthly Income, 2018	0.0227*	-0.00115	-0.0839	0.448
	(1.75)	(-0.08)	(-0.60)	(0.31)
Sample	All Gains	<80 ptile Gains	[80,99) ptile Gains	>99 ptile Gains
Observations	4,878	3,902	927	49
Adj. R^2	0.112	0.000	0.035	-0.051

Table 3

Crypto Gains and Spending

This table shows the marginal propensity to consume (MPC) out of crypto wealth following the run-up in prices Bitcoin in 2017. The dependent variable is the sum of total spending in 2018. 12-month crypto gains is the dollar amount realized and unrealized in crypto wealth from the end of 2016 to 2017. Average monthly income in 2017 is included as a control. Column (1) estimates the MPC for the entire sample of users. Columns (2)–(4) use subsamples that include non-crypto users and crypto users with gains below the 80^{th} percentile, 80^{th} to 99^{th}, and above 99^{th}, respectively. *t*-statistics in parentheses are heteroskedasticity-robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	12-Month post-Peak Total Spending			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
12-Month Crypto Gains, December 2017	0.210***	0.118	0.284***	0.0463*
	(6.32)	(0.12)	(5.56)	(1.92)
Average Monthly Income, 2018	5.552***	5.792***	5.801***	5.800***
	(109.95)	(83.60)	(82.46)	(82.16)
Sample	All Gains	<80 ptile Gains	[80,99) ptile Gains	>99 ptile Gains
Observations	100,652	99,676	96,701	95,823
Adj. R^2	0.172	0.154	0.154	0.154

Table 4

Heterogeneous Effects

This table tests consumption sensitivity to crypto wealth for users that adopt crypto during the run-up and for users that have low liquidity. The dependent variable is the sum of total spending in 2018. 12-month crypto gains is the dollar amount realized and unrealized in crypto wealth from the end of 2016 to 2017. Crypto run-up adopters are users that invest in crypto after June 2017. Low Available Balance is an indicator equal to 1 for users with average checking balances below $1,000 in 2017. Overdraft in 2017 is an indicator equal to 1 if the user were charged an overdraft fee in 2017. Average monthly income in 2017 is included as a control. *t*-statistics in parentheses are heteroskedasticity-robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	12-Month post-Peak Total Spending	12-Month post-Peak Total Spending	
	OLS	OLS	OLS
	(1)	(2)	(3)
12-Month Crypto Gains, December 2017	0.197***	0.206***	0.174***
	(5.74)	(6.18)	(5.20)
Average Monthly Income, 2018	5.550***	5.524***	5.587***
	(109.90)	(109.04)	(109.62)
Crypto Run-up Adopter	914.5		
	(1.08)		
Crypto Run-up Adopter × Crypto Gains	0.267*		
	(1.85)		
Low Available Balance		-13,515***	
		(-20.58)	
Low Available Balance × Crypto Gains		0.755***	
		(3.23)	
Overdraft in 2017			3,511***
			(7.82)
Overdraft in 2017 × Crypto Gains			0.335***
			(2.73)
Observations	100,652	100,652	100,652
Adj. R^2	0.172	0.174	0.173

Table 5

Propensity to Consume Out of Crypto Wealth

This table shows the marginal propensity to consume (MPC) out of crypto wealth for various spending categories following the run-up in Bitcoin prices in 2017. 12-month crypto gains is the dollar amount of crypto wealth, both realized and unrealized, from the end of 2016 to 2017. Average monthly income in 2017 is included as a control. t-statistics in parentheses are heteroskedasticity-robust. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	12-Month Spending, post-Peak				
	Total	Auto	Cable/Telecom	Cash/Check	Charity
	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
12-Month Crypto Gains, December 2017	0.210***	0.00213	-0.00316***	0.130***	0.000966
	(6.32)	(1.44)	(-3.20)	(6.01)	(1.37)
Average Monthly Income, 2018	5.552***	0.155***	0.155***	1.746***	0.0331***
	(109.95)	(58.18)	(75.35)	(49.53)	(27.46)
Observations	100,652	100,652	100,652	100,652	100,652
Adj. R^2	0.172	0.050	0.074	0.054	0.014

	12-Month Spending, post-Peak				
	Education	Entertainment /Travel	General Merchandise	Groceries	Insurance
	OLS	OLS	OLS	OLS	OLS
	(6)	(7)	(8)	(9)	(10)
12-Month Crypto Gains, December 2017	-0.000108	0.0214***	0.0136**	-0.0000680	0.00210
	(-0.16)	(5.93)	(2.29)	(-0.03)	(1.35)
Average Monthly Income, 2018	0.0628***	0.336***	0.940***	0.286***	0.170***
	(27.03)	(60.60)	(85.68)	(64.11)	(53.30)
Observations	100,652	100,652	100,652	100,652	100,652
Adj. R^2	0.017	0.070	0.116	0.064	0.047

	12-Month Spending, post-Peak				
	Medical	Mortgage	Rent	Restaurants	Utilities
	OLS	OLS	OLS	OLS	OLS
	(11)	(12)	(13)	(14)	(15)
12-Month Crypto Gains, December 2017	0.00254***	0.0158**	0.00357*	0.00793***	0.00406***
	(2.69)	(2.36)	(1.94)	(3.45)	(2.97)
Average Monthly Income, 2018	0.0643***	1.002***	0.0467***	0.281***	0.163***
	(42.43)	(73.88)	(15.80)	(64.48)	(75.65)
Observations	100,652	100,652	100,652	100,652	100,652
Adj. R^2	0.029	0.096	0.003	0.069	0.081

Table 6

Crypto Withdrawals and Expenditures

This table presents event study regressions at the account-month level. The event is defined as the first time an account takes a withdrawal from an exchange greater than $1,000. 25 total months (12 pre- and 12 post-) are included for treated accounts and the entire observed time series is included for untreated. Controls and fixed effects are included as indicated. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the account level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Annualized Monthly Spending				
	Total	Auto	Cable/Telecom	Cash/Check	Charity
	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
Post First Crypto Withdrawal, >$1,000	1,451***	5.737	8.918	696.0*	4.087
	(2.61)	(0.12)	(0.37)	(1.73)	(0.32)
Average Monthly Income, Prior 12-Months	2.804***	0.0940***	0.0868***	0.863***	0.0109***
	(99.23)	(51.80)	(39.84)	(32.20)	(16.06)
Account FE	X	X	X	X	X
Month FE	X	X	X	X	X
Observations	11,607,112	11,607,112	11,607,112	11,607,112	11,607,112
Adj. R^2	0.557	0.239	0.468	0.391	0.375

	Annualized Monthly Spending				
	Education	Entertainment /Travel	General Merchandise	Groceries	Insurance
	OLS	OLS	OLS	OLS	OLS
	(6)	(7)	(8)	(9)	(10)
Post First Crypto Withdrawal, >$1,000	-0.379	53.43	-55.83	-177.2***	80.42**
	(-0.02)	(0.62)	(-0.34)	(-3.26)	(2.13)
Average Monthly Income, Prior 12-Months	0.0133***	0.152***	0.547***	0.159***	0.0704***
	(13.31)	(46.98)	(75.14)	(59.12)	(35.68)
Account FE	X	X	X	X	X
Month FE	X	X	X	X	X
Observations	11,607,112	11,607,112	11,607,112	11,607,112	11,607,112
Adj. R^2	0.227	0.286	0.418	0.515	0.424

	Annualized Monthly Spending				
	Medical	Mortgage	Rent	Restaurants	Utilities
	OLS	OLS	OLS	OLS	OLS
	(11)	(12)	(13)	(14)	(15)
Post First Crypto Withdrawal, >$1,000	10.65	479.3***	34.87	19.24	86.73***
	(0.45)	(3.03)	(0.63)	(0.31)	(3.02)
Average Monthly Income, Prior 12-Months	0.0341***	0.442***	0.0343***	0.167***	0.0848***
	(34.87)	(50.67)	(17.57)	(62.33)	(60.80)
Account FE	X	X	X	X	X
Month FE	X	X	X	X	X
Observations	11,607,112	11,607,112	11,607,112	11,607,112	11,607,112
Adj. R^2	0.251	0.538	0.239	0.445	0.419

Table 7

Crypto Withdrawals and Housing Consumption

This table presents event study regressions similar to those of Table 6 but uses monthly mortgage spending and monthly rent spending in the left-hand side for columns (1)–(3) and (4)–(6), respectively. Columns (2) and (5) define an event as a first crypto exchange withdrawal in excess of $5,000 and columns (3) and (6) define an event as a first Coinbase withdrawal in excess of $10,000. Controls and fixed effects are included as indicated. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the account level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Annualized Monthly Mortgage Spending			New Homeowner	Buy Bigger House
	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
Post First Crypto Withdrawal, >$1,000	479.3***			0.0103*	0.0147***
	(3.03)			(1.86)	(2.67)
Post First Crypto Withdrawal, >$5,000		954.0***			
		(3.18)			
Post First Crypto Withdrawal, >$10,000			1,023**		
			(2.57)		
Average Monthly Income, Prior 12-Months	0.442***	0.443***	0.444***	-0.00000203***	0.00000256***
	(50.67)	(51.54)	(51.71)	(-17.61)	(14.45)
Account FE	X	X	X	X	X
Month FE	X	X	X	X	X
Observations	11,607,112	11,793,096	11,840,428	11,607,112	11,607,112
Adj. R^2	0.538	0.536	0.535	0.154	0.336

Table 8

Bitcoin Run-Up Diff-In-Diff: County-Month Housing Prices

This table presents difference-in-difference estimates of the effect of Bitcoin price appreciation on house prices. Observations are at a county-month level; the dependent variable is the natural logarithm of the monthly 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 September 2017, when counties experienced a spike in crypto withdrawals (see Figure 11). The sample is limited to the six months before and after October 2017. Columns (1) and (3) define treated counties as top tercile 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. 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.

	County-Month Log Median Housing Price ($100k)		County-Month Log Median Housing Price ($100k)	
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
High Crypto Wealth County × Post Run-up	0.000329**		0.000320**	
	(2.37)		(2.25)	
Log County Crypto Wealth × Post Run-up		0.000115***		0.000114**
		(2.65)		(2.54)
High Crypto Wealth County	-0.000445***			
	(-3.60)			
Post Run-up	0.0000498	0.0000483		
	(0.49)	(0.57)		
Log County Crypto Wealth		-0.000130***		
		(-3.56)		
1 Month House Price Lag	X	X	X	X
County FE			X	X
Month FE			X	X
Observations	26,341	33,378	26,336	33,373
Adj. R^2	1.000	1.000	1.000	1.000

Table 9

Effect of Crypto Gains on Housing Prices

This table presents instrumental variable estimates of the effect of crypto gains on 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 Bitcoin net return (see Equation 9). 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 Bitcoin return (i.e., Bitcoin return adjusted for market returns as in Equation 10). Observations are at the county-month level starting in 2015. 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 6 Months	Next 12 Months	Next 6 Months	Next 12 Months	Next 6 Months	Next 12 Months
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Per Capita Crypto Gains, Prior 12-Months	0.168**	0.451**	0.180**	0.414**	0.186**	0.385**
	(2.43)	(2.16)	(2.42)	(2.20)	(2.51)	(2.48)
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	195,969	180,974	195,968	180,974	195,968	180,974
Weak ID KP F Stat	7,260	3,028	8,128	4,391	1,912	5,922

Internet Appendix

A.1 Internet Appendix

Internet Appendix

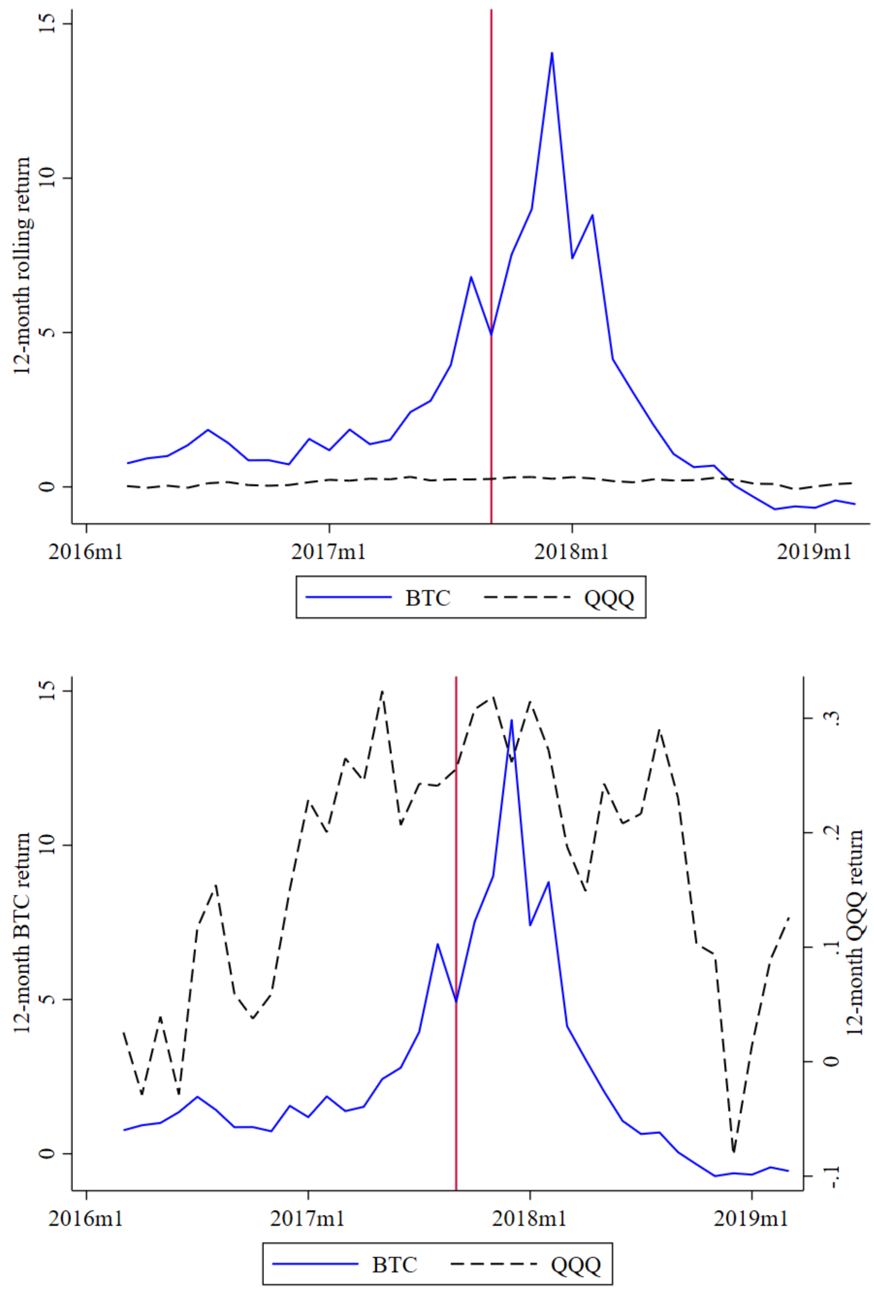


Figure A.1. Bitcoin and Nasdaq Rolling 12-month Returns. This figure shows the 12-month holding period returns each month for holding Bitcoin and the Nasdaq (QQQ). The top panel plots these returns on the same scale to demonstrate the outsized performance of Bitcoin. The bottom panel plots the returns on separate axes, with Bitcoin returns on the left axis. The red line in the figures indicates the pre- and post- periods used in difference-in-differences analysis related to the Bitcoin Run-up at the end of 2017, which we define based on the spike in county-level crypto withdrawals.

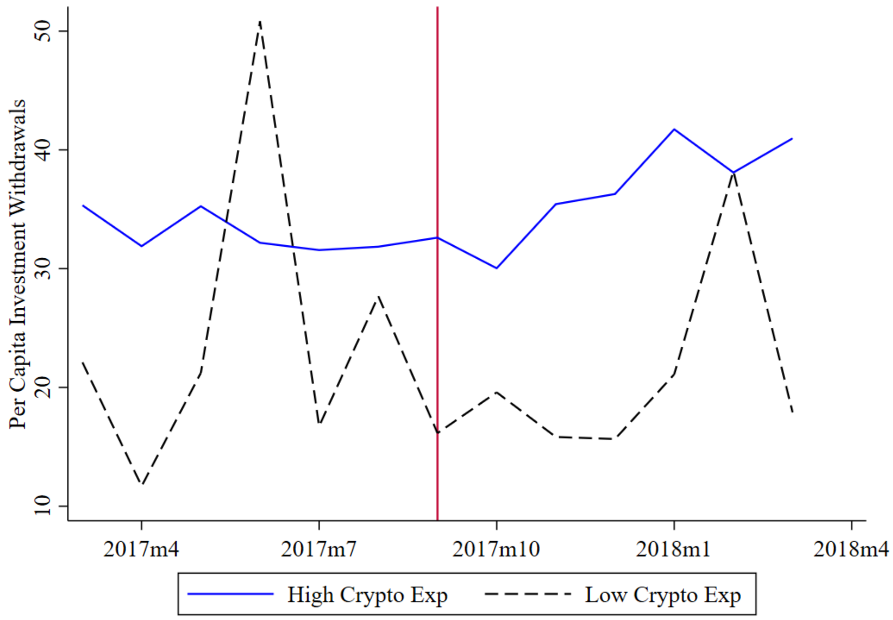


Figure A.2. Equity Investment Withdrawals around Bitcoin Run-up by Crypto Exposure. This figure shows per capita withdrawals from traditional equity investments each month separately for high and low crypto exposure counties. Investment withdrawals are identified as credits to the user's account from retail trading platforms such as Fidelity, Charles Schwabb, Robinhood, Acorns, etc.

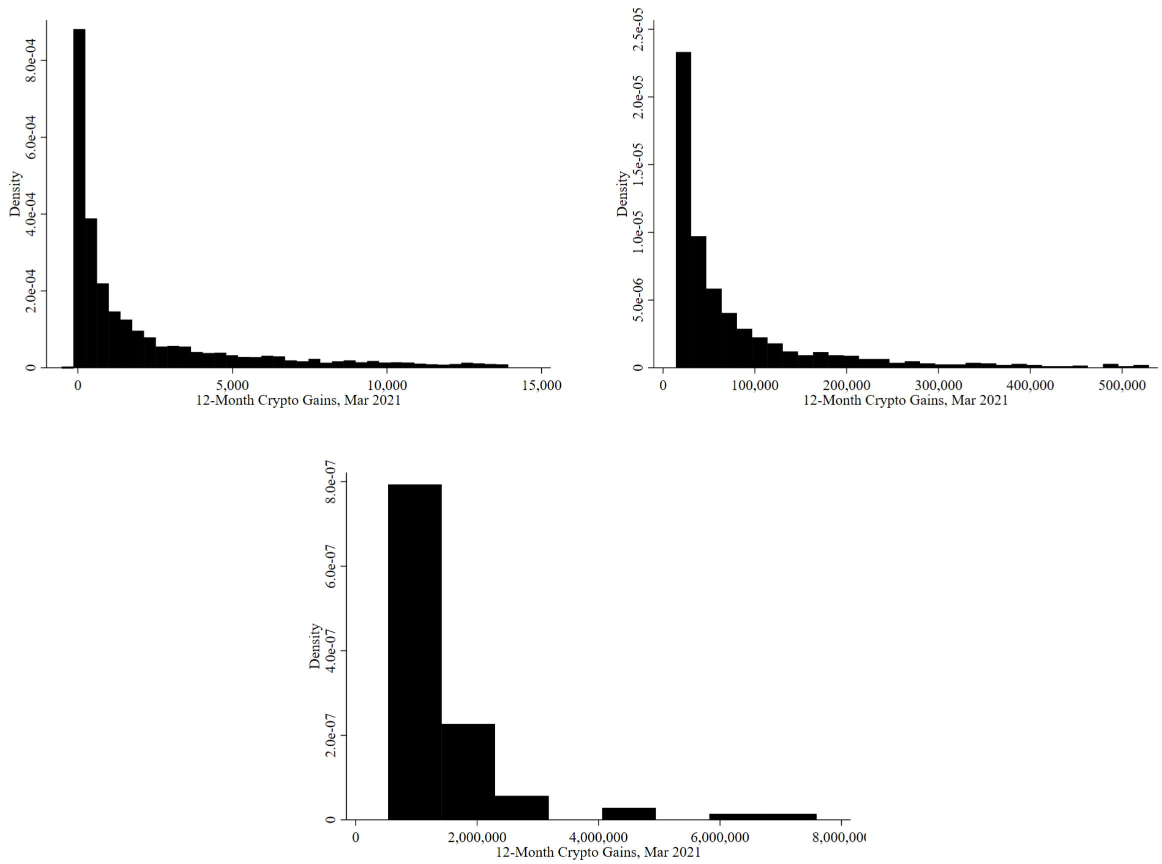


Figure A.3. Distribution of 12-month Crypto Gains in March 2021. This figure shows the distribution of gains over the prior 12- months in March of 2021. The distribution is divided into three groups. Panel (a) shows the gains in the bottom 80th percentile. Panel (b) shows the 80th percentile to the 99th percentile. Panel (c) shows those greater than the 99th percentile.

Table A.1

Crypto Gains and Investment—Second Runup

This table shows the effects similar to the ones documented in Table 2 for the second run-up in Bitcoin prices. Controls and fixed effects are included as indicated. t-statistics in parentheses are heteroskedasticity-robust and clustered at the account level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Crypto Deposits

	12-Month post-Peak Gross Crypto Deposits			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
12-Month Crypto Gains, March 2021	0.0197***	0.657***	0.0914***	0.00988***
	(17.60)	(8.96)	(5.67)	(4.02)
Crypto Deposits, prior 12-months	0.0307***	0.0423***	0.0576***	0.0295***
	(18.39)	(7.23)	(2.85)	(5.30)
Average Monthly Income, following 12-months	0.0168***	0.0244***	0.0300**	0.0149***
	(8.12)	(3.75)	(2.51)	(2.74)
Sample	All Gains	<80 ptile Gains	[80,99) ptile Gains	>99 ptile Gains
Observations	77,312	75,727	70,895	69,470
Adj. R^2	0.081	0.028	0.061	0.025

Panel B: Investment Deposits

	12-Month post-Peak Investment Deposits			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
12-Month Crypto Gains, March 2021	0.00213	0.0506	0.00865*	-0.000462
	(1.05)	(0.98)	(1.87)	(-0.44)
Investment Deposits, prior 12-months	0.613***	0.614***	0.609***	0.604***
	(70.26)	(24.80)	(23.43)	(22.63)
Average Monthly Income, following 12-months	0.239***	0.289***	0.297***	0.289***
	(25.13)	(18.15)	(17.85)	(17.44)
Sample	All Gains	<80 ptile Gains	[80,99) ptile Gains	>99 ptile Gains
Observations	77,312	75,727	70,895	69,470
Adj. R^2	0.340	0.348	0.356	0.343

Panel C: Crypto Withdrawals

	12-Month post-Peak Gross Crypto Withdrawals			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
12-Month Crypto Gains, March 2021	0.00954***	0.115***	0.0312***	0.00238
	(7.38)	(4.30)	(2.64)	(0.72)
Crypto Deposits, prior 12-months	0.0237***	0.0338**	0.147	-0.0334
	(4.30)	(2.32)	(1.54)	(-0.41)
Average Monthly Income, following 12-months	0.0284**	0.0340**	-0.394	-0.0693
	(2.53)	(2.07)	(-0.82)	(-0.15)
Sample	All Gains	<80 ptile Gains	[80,99) ptile Gains	>99 ptile Gains
Observations	7,922	6,337	1,505	80
Adj. R^2	0.041	0.018	0.002	-0.029

Table A.2

Crypto Gains and Spending—Second Runup

This table shows the effects similar to the ones documented in Table 3 for the second run-up in Bitcoin prices. Controls and fixed effects are included as indicated. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the account level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	12-Month post-Peak Total Spending			
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
12-Month Crypto Gains, March 2021	0.0379***	0.341*	0.0490***	0.00624
	(4.22)	(1.90)	(3.92)	(1.58)
Average Monthly Income, following 12-months	4.933***	5.082***	5.077***	5.101***
	(110.44)	(92.22)	(88.14)	(88.04)
Sample	All Gains	<80 ptile Gains	[80,99) ptile Gains	>99 ptile Gains
Observations	77,312	75,727	70,895	69,470
Adj. R^2	0.193	0.184	0.182	0.184

Table A.3

Heterogeneous Effects—Second Runup

This table shows the effects similar to the ones documented in Table 4 for the second run-up in Bitcoin prices. Controls and fixed effects are included as indicated. t-statistics in parentheses are heteroskedasticity-robust and clustered at the account level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	12-Month post-Peak Total Spending	12-Month post-Peak Total Spending	
	OLS	OLS	OLS
	(1)	(2)	(3)
12-Month Crypto Gains, March 2021	0.0376***	0.0374***	0.0333***
	(4.17)	(4.14)	(3.60)
Average Monthly Income, following 12-months	4.932***	4.921***	4.938***
	(110.37)	(109.84)	(109.61)
Crypto Run-up Adopter	362.0		
	(0.38)		
Crypto Run-up Adopter × Crypto Gains	0.0408		
	(0.35)		
Low Available Credit Balance		-5,723***	
		(-6.99)	
Low Available Credit Balance × Crypto Gains		0.0361	
		(0.56)	
Overdraft in prior 12-months			735.9
			(1.21)
Overdraft in prior 12-months × Crypto Gains			0.0657*
			(1.73)
Observations	77,312	77,312	77,312
Adj. R^2	0.193	0.193	0.193

Table A.4

Crypto Gains and Investment/Spending

Controls and fixed effects are included as indicated. t-statistics in parentheses are heteroskedasticity-robust and clustered at the account level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: First Run-up

	12-Month post-Peak Total Spending	12-Month post-Peak Gross Crypto Deposits	12-Month post-Peak Gross Crypto Withdrawals	12-Month post-Peak Investment Deposits
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
12-Month Crypto Gains, December 2017	0.200***	0.00578***	0.000433***	0.0102**
	(5.93)	(11.87)	(4.19)	(2.03)
Average Monthly Income, prior 12-months	5.788***	0.00145***	0.000930	0.0992***
	(106.96)	(6.43)	(1.42)	(14.72)
Crypto Run-up Adopter	800.9	363.8***	6.642	552.9***
	(0.92)	(31.11)	(1.13)	(4.93)
Crypto Run-up Adopter × Crypto Gains	0.455**	0.0151***	0.00151**	0.00125
	(2.35)	(4.86)	(2.25)	(0.05)
Investment Deposits 2017				0.720***
				(77.03)
Observations	100,652	100,652	4,878	100,652
Adj. R^2	0.168	0.138	0.008	0.398

Panel B: Second Run-up

	12-Month post-Peak Total Spending	12-Month post-Peak Gross Crypto Deposits	12-Month post-Peak Gross Crypto Withdrawals	12-Month post-Peak Investment Deposits
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
12-Month Crypto Gains, prior 12-months	0.0371***	0.0203***	0.00137***	0.00218
	(4.12)	(17.93)	(8.07)	(1.07)
Average Monthly Income, prior 12-months	4.893***	0.0221***	0.00558***	0.201***
	(103.01)	(10.59)	(2.71)	(20.70)
Crypto Run-up Adopter	851.9	2271.3***	58.89***	545.0***
	(0.89)	(22.73)	(3.21)	(2.87)
Crypto Run-up Adopter × Crypto Gains	0.0333	0.0550**	0.00226	-0.00641
	(0.25)	(2.22)	(0.81)	(-0.31)
Investment Deposits prior 12-months				0.615***
				(70.08)
Observations	77,312	77,312	7,922	77,312
Adj. R^2	0.174	0.107	0.019	0.336

Table A.5

Second Bitcoin Run-up and Expenditures

Controls and fixed effects are included as indicated. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the account level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	12-Month Spending, post-Peak				
	Total	Auto	Cable/Telecom	Cash/Check	Charity
	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
12-Month Crypto Gains, March 2021	0.0379***	-0.000253	-0.00183***	0.0242***	0.000363
	(4.22)	(-0.47)	(-5.96)	(5.46)	(1.41)
Average Monthly Income, following 12-months	4.933***	0.158***	0.129***	1.225***	0.0370***
	(110.44)	(51.77)	(63.00)	(50.22)	(24.48)
Observations	77,312	77,312	77,312	77,312	77,312
Adj. R^2	0.193	0.046	0.064	0.059	0.013

	12-Month Spending, post-Peak				
	Education	Entertainment /Travel	General Merchandise	Groceries	Insurance
	OLS	OLS	OLS	OLS	OLS
	(6)	(7)	(8)	(9)	(10)
12-Month Crypto Gains, March 2021	-0.000144	0.00432***	-0.000578	-0.00330***	0.00197***
	(-0.45)	(4.39)	(-0.25)	(-4.38)	(3.62)
Average Monthly Income, following 12-months	0.0679***	0.279***	1.011***	0.276***	0.155***
	(25.78)	(54.36)	(75.54)	(54.11)	(52.67)
Observations	77,312	77,312	77,312	77,312	77,312
Adj. R^2	0.018	0.062	0.107	0.054	0.053

	12-Month Spending, post-Peak				
	Medical	Mortgage	Rent	Restaurants	Utilities
	OLS	OLS	OLS	OLS	OLS
	(11)	(12)	(13)	(14)	(15)
12-Month Crypto Gains, March 2021	0.0000303	0.00959***	0.0000372	-0.000273	0.00112***
	(0.11)	(4.13)	(0.09)	(-0.31)	(2.71)
Average Monthly Income, following 12-months	0.0625***	0.936***	0.0477***	0.286***	0.155***
	(39.37)	(72.16)	(15.12)	(56.61)	(75.17)
Observations	77,312	77,312	77,312	77,312	77,312
Adj. R^2	0.029	0.104	0.004	0.061	0.092

Table A.6

Effect of Crypto Gains on Housing Prices—2SLS Breakdown

This table reports results related to columns (3) and (5) of Table 9. 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 9, respectively, and columns (3) and (5) present the relevant first stages for columns (3) and (5) of Table 9. Observations are at the county-month level starting in 2015. 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 6 Months	Change in House Price Index, Next 6 Months	Per Capita Crypto Gains, Prior 12 Months	Change in House Price Index, Next 6 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	0.173***				
	(2.68)				
Passive Gains		0.180**	1.004***		
		(2.41)	(90.16)		
Excess Passive Gains				0.341**	1.835***
				(2.50)	(43.72)
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	195,968	195,968	195,968	195,968	195,968
Adj. R^2	0.640	0.640	0.915	0.640	0.860

Table A.7

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 9, 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 Bitcoin return (or excess Bitcoin return) over the prior 12-months. Observations are at the county month level starting in 2015. 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 6 Months	Next 12 Months	Next 6 Months	Next 12 Months	Next 6 Months	Next 12 Months
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Per Capita Crypto Gains, Prior 12-Months	0.134**	1.082**	0.135*	0.653*	0.135*	0.445*
	(2.03)	(2.29)	(1.90)	(1.92)	(1.95)	(1.87)
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	165,773	150,791	165,768	150,786	165,768	150,786
Weak ID KP *F* Stat	551.1	280.7	455.3	223.2	580.5	276.1