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Cryptocurrency Investing: Stimulus Checks and Inflation Expectations[*]

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ABSTRACT

We provide a first look into the factors that affect retail investing in cryptocurrencies. We use consumer transaction data to examine how borrower characteristics, liquidity shocks, and hedging requirements shape crypto investment decisions of millions of U.S. individuals. We find that – similar to traditional investing – crypto investing responds to wealth, risk attitude, and liquidity constraints. Yet, crypto investing is more responsive than after-tax traditional investment flows to overall markets conditions. We then show that investors' budget constraints affect crypto investing, in line with portfolio choice theories. We find that relaxing the budget constraint through receiving stimulus payments increases crypto investing. Tighter future budget due to higher expected inflation also increases crypto investing, consistent with hedging motives. Our findings are important for understanding this new high-risk, high-return asset class and designing effective regulations in this rapidly evolving space.

Keywords: Consumer finance, cryptocurrency, FinTech, inflation, portfolio choice, stimulus

JEL classification: G51, G23, G38, G11, E42, E31

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I. Introduction

The global value of cryptocurrencies has grown rapidly over the past years, peaking at close to $3 trillion by market cap in late 2021.[1] While still relatively small compared to investments in other asset classes like the $125 trillion equity market, cryptocurrency investing and its rapid growth have grabbed the attention of policy makers throughout the world.[2]

One of the key concerns around cryptocurrency investing is that consumers are potentially exposing themselves to risks that they are not aware of, jeopardizing their overall financial health. This concern is magnified by the uncertainty surrounding *who* is currently investing in this nascent space. Although transactions and (some) digital wallet data are publicly available, they do not provide information about who is behind these transactions. Are wealthy individuals diversifying their portfolios into a new asset class? Are low-income consumers allocating their limited funds in hopes for a lottery-style win? Are these investments perceived as safe hedges against changes in market conditions? We provide some first answers to these key questions, which can help inform policy responses to this rapidly growing space.

Given existing data limitations, is has only been possible to speculate about the drivers of the rapid increase in retail participation in the crypto industry. It is widely believed that the large increase in cryptocurrency wealth is a result of a retail "investing mania" and fear of missing out (FOMO).[3] Others suggest that the low interest rate environment and cheap liquidity are key drivers of crypto investing. Finally, some theories suggest that the fixed supply of cryptocurrency make it a good inflation hedge.[4]

While each of these idiosyncratic and macro drivers likely propel retail cryptocurrency investment to some extent, we lack a rigorous analysis of their magnitudes and their heterogeneous effects across households. Additionally, it has been challenging to observe how this vast increase in cryptocurrency wealth has filtered through to the general economy, which in turn makes it difficult to predict its impact on consumers and overall economic activity.

In this paper, we shed light on the drivers of retail cryptocurrency investment by mak-

[1]See https://fortune.com/2021/11/09/cryptocurrency-market-cap-3-trillion-bitcion-ether-shiba-inu/.

[2]See the March 2022 executive order on "Ensuring Responsible Development of Digital Assets" available at https://www.whitehouse.gov/briefing-room/presidential-actions/2022/03/09/executive-order-on-ensuring-responsible-development-of-digital-assets.

[3]See for instance https://www.nytimes.com/2021/03/13/technology/crypto-art-NFTs-trading-cards-investment-manias.html.

[4]See https://www.newsweek.com/hedge-funds-turning-bitcoin-consumers-keeping-cars-longer-1600965, which became especially relevant as CPI jumped to 7% from December 2020 to December 2021. Also see https://www.bls.gov/opub/ted/2022/consumer-price-index-2021-in-review.htm.

ing use of unique transaction-level data for a representative sample composed of millions of individuals in the U.S. over several years. We identify individual cryptocurrency purchases and sales by observing transactions directly into and out of user bank and credit card accounts from the largest cryptocurrency investing avenues in the U.S., such as cryptocurrency trading platforms and exchanges like Coinbase.[5]

Although transactions in cryptocurrencies are recorded in publicly available blockchains, consumer financial transaction data has several advantages. First, our data allows us to observe both cryptocurrency investors and non-investors (and their financial characteristics). While blockchain data provides detailed information about transactions, it cannot provide any insight into who is behind an anonymous wallet address and who has never invested in cryptocurrencies. As we describe in detail below, we identify cryptocurrency investing via deposits to (i.e., debits) and withdrawals from (i.e., credits) major cryptocurrency trading venues, which we obtain through transaction descriptions in bank and credit card accounts. Second, the granularity of our data allows us to obtain a more holistic view of investors' finances: observing income, spending, and other types of investments. Since we observe all of the transactions in a user bank and credit account, we can also identify numerous other key transactions, such as whether the investors received stimulus payments. Finally, the data are in part directly provided by the major U.S. banks which disclose these transactions to a data aggregator, ensuring that the data do not suffer from the common active selection concerns related to investors having to join a specific financial planning platform to observe their information. Overall, our data set enables us to obtain the first granular view of retail cryptocurrency investing and allows us to fill a gap in the existing literature and policy discourse by shedding light on the factors that drive these investments.

We begin our analysis by documenting several key facts about cryptocurrency investments. The first hypothesis we test is whether the performance of the major cryptocurrency, Bitcoin, contributed to the subsequent entry of new investors in the space. We observe a tight correlation between crypto investments and the price and returns of Bitcoin on both the extensive and intensive margin. Specifically, we find that investors rapidly entered the market in 2017 during the first large run-up in Bitcoin prices, and investing demand began to increase rapidly again after the onset of the Covid-19 pandemic in lockstep with the performance of Bitcoin. In contrast, we do not find such a tight relationship when we look at transaction in traditional brokerage accounts and their correlation with the performance of the equity markets. Most of the investments we document are concentrated in the most populous states, such as California and New York, but the peaks in investment growth have been much more widespread across the United States.

[5]As of January 2022, Coinbase routed more than 65% of the crypto transaction volume in the U.S.

We next provide details of characteristics of cryptocurrency investors. We do this in two ways: by exploring the information that can be observed by analyzing the investors' transactions, as well as by complementing the data with zip-level characteristics. One of the key questions about crypto markets is whether the exuberance of the 2020-2022 period was partly based on the entry of less and less sophisticated investors, i.e. the "greater fool" theory. We test this conjecture by comparing the financial characteristics of investors that entered the market early on compared to those that started investing in crypto at the peak. Specifically, we look at their income, several measures of financial constraints, and indicators for their attitudes towards risk.

Overall, when we compare crypto investors with non-crypto investors, we find that crypto investors are more likely to have higher income, are twice as likely to have ever gambled, are more likely to be homeowners and spend more in general and via credit cards in particular. We also find that early crypto adopters, defined as those who invest for the first time prior to the 2017 BTC price run up, are more likely to have gambled, incur overdrafts and spend more in general than those who are later adopters of cryptocurrency investing.Additionally, crypto users live in more educated places and for early crypto adopters, they are more likely to be located in wealthier zip codes with a higher concentration of professional industries and managerial occupations. Overall, these results suggest that while in general crypto investors exhibit higher income and higher financially stability, this is even more so for the investors that adopted earlier rather than later. However, we do find that early adopters withdraw crypto during the first boom period in 2017, while newer adopters piled in at that time.

Having explored the investors' characteristics driving their investment decisions, we now turn to the analysis of investors' propensity to invest in riskier asset classes, like crypto, out of temporary increases in liquidity. On the one hand, investors might perceive increased liquidity as an opportunity to take risk by investing in assets that they would not have invested in otherwise, which might be consistent with the spirit of expansionary policies. On the other hand, it is also plausible that more fragile investors taking advantage of this liquidity by improving their financial health. To explore these questions, we exploit the fiscal measures enacted during the Covid 19 pandemic as a laboratory. One of the most significant interventions was the payment of stimulus checks to millions of households in the US, who received money regardless of whether they were experiencing financial hardship. The funds were delivered in three separate checks: the first one in April 2020 (Stimulus I), the second in December 2020 (Stimulus II), and the last one in March 2021 (Stimulus III). These checks were sizable, with amounts of $1,200, $600 and $1,400, per eligible adult respectively. We analyze the marginal propensity to invest (MPI) in both crypto and traditional equity accounts out of this additional liquidity and explore its heterogeneity.

We find that the largest MPI in crypto in response to the first stimulus payments is driven by those who are more likely to live hand-to-mouth(i.e. low available liquidity) and incur overdrafts and hence more likely to be ex ante liquidity constrained. This is somewhat surprising because we could have expected these investors to use these funds to improve their finances. We find little MPI response to the second stimulus payment but again find that hand-to-mouth consumers have a higher propensity to invest in cryptocurrency out of Stimulus III payments. Overall, across all three stimulus payments, we find that for every \$1 of stimulus payments, around \$0.005 is invested in cryptocurrency, however, the investors who adopted crypto post Covid exhibit an MPI of \$0.0140 for every \$1 of stimulus. This is in contrast to MPIs for investments in traditional assets of \$0.008 and \$0.0144 for the full sample of crypto investors and Covid adopters, respectively. While the MPI into crypto is smaller than for traditional investments in an absolute sense, the ratio of crypto investment to traditional investment is much higher following these stimulus checks than during previous periods. That said, while these MPI's are significant and robust to a variety of specifications, they are relatively small—suggesting that while stimulus payments may have encouraged entry to the crypto markets, they did not cause a significant diversion of funds to cryptocurrency in the aggregate.

The last step in our analysis puts crypto investment into the broader macroeconomic picture to further try to identify the key factors driving entry in this market. The unprecedented fiscal measures adopted during the Covid pandemic, combined with pandemic related supply chain disruptions, have also thrown inflation concerns at the center of the policy debate. While cryptocurrencies – and especially Bitcoin – have long been depicted as a way to hedge against spikes in inflation, we have scant evidence of how individual consumers view crypto investments in relation to their own expectations of inflation.

We are able to tackle this question by making use of our rich set of transaction-level data and proceed in two steps. We first make use of inflation expectation surveys at the aggregate level and document a strong positive relation between inflation expectations and investments in crypto assets. We then use ex-ante consumption baskets (measured over the 12 months prior) to create individual-level proxies for inflation expectations. Our individual level measure makes use of the fact that price changes of goods in consumers' personal expenditure bundles are likely to drive the formation of individuals' inflation expectations (e.g., Malmendier and Nagel, 2016; D'Acunto, Malmendier, Ospina, and Weber, 2021). For example, those who spend a higher fraction of total expenditure on gas and groceries might have heightened expectations of future inflation because gas and grocery prices have increased significantly in the recent past.

Using this individual-level measure of inflation expectations, we also find that higher inflation expectations result in increased cryptocurrency investment, even after controlling for time-varying factors specific to people living within the same state and earning similar incomes. This effect is stronger for more sophisticated individuals, gamblers, Covid adopters, and less pronounced for early crypto adopters. We also find that this effect is particularly pronounced amongst lower income-consumers, those with more unstable income and those overall more liquidity constrained. These results combined indicate that abundance of liquidity and concerns about inflation contribute to cryptocurrency adoption and investment at both the extensive and intensive margins.

The literature surrounding cryptocurrency investments has been expanding rapidly. Some of these papers directly utilize on-chain data. For example, Makarov and Schoar (2021) document the concentration and regional composition of the miners in the Bitcoin blockchain and analyze the ownership concentration of the largest holders of Bitcoin. Lehar and Parlour (2020) provides evidence of potential collusion among miners.

Some papers have investigated crypto markets under the lens of asset pricing. For instance, Liu and Tsyvinski (2021) shows that cryptocurrency returns are driven by factors that are specific to cryptocurrency markets such as user adoption of cryptocurrencies and the costs of cryptocurrency production. Liu, Tsyvinski, and Wu (2022) finds that three factors – cryptocurrency market, size, and momentum – capture the cross-section of expected cryptocurrency returns. Others have investigated the extent to which market frictions create arbitrage opportunities in crypto markets (see, for instance, Makarov and Schoar, 2020), how price discovery occurs (Makarov and Schoar, 2019), and the presence of wash trading (Cong, Li, Tang, and Yang, 2021).

We contribute to this literature by analyzing the crypto market through the lenses of the retail investors allocating funds to this nascent asset class. We provide the first characterization of the investors and what drives their crypto investments. We take a holistic approach by examining the key factors driving their portfolio choice decision: risk preferences, liquidity and hedging needs. In doing so, we also provide evidence against the common view that the recent increase in prices exhibited bubble features and that the fiscal measures aimed at increase household liquidity were behind the crypto run-up in 2020 and onward. The analysis pertaining to the role of inflation and inflation expectations in crypto investment also builds on the literature studying how beliefs affect investors' expectations and portfolio choices. Giglio, Maggiori, Stroebel, and Utkus (2020), for instance, show that retail investors' beliefs are incorporated in their asset allocation decisions using survey evidence and data on traditional investments. Also related are the studies on inflation by Malmendier and Nagel (2016) and D'Acunto et al. (2021) which inform our individual measure of exposure to inflation.

The rest of this paper is organized as follows. The next Section II introduces the data and describes how the main variables in our analysis are computed. Section III presents several key facts about crypto investments that exploit the granularity of our data. Sections IV and V present the main findings about the role played by stimulus checks and inflation expectations in driving crypto investments. Section VI concludes.

II. Data

In this Section, we describe our data sources, the process of identifying cryptocurrency transactions, and our key measures, such as stimulus payments and inflation exposure.

A. Transaction Level Data

Our main data source comprises de-identified transaction data from bank and credit card accounts for over 59 million U.S. consumers from January 2010 to May 2021. The data are unbalanced as consumers can enter and exit the panel. Still, we observe around 10.6 million consumers per month, on average throughout the panel. In addition to the consumer transaction data, we obtained monthly demographics panel data for these consumers, which includes their income range and city/state of residence, from January 2014 to May 2021.

The data are proprietary and come from a large U.S. data aggregation and analytics platform. The data provider assists financial institutions and FinTech firms, including several top U.S. banks, in providing personal financial management services to their wealth management and retail banking clients. This collaboration enables users to track financial accounts (e.g., bank accounts, credit cards, retail reward accounts) and view consumption-related insights. The platform also uses machine learning techniques to categorize data by spending category, merchant, payment mode, and other dimensions. These data – in aggregated and disaggregated forms – can then be offered as a product to institutional investors and academics.

Importantly, the platform provides access to these data based on agreements with the platform's bank partners and non-bank institutions rather than with consumers. This institutional detail makes the data more comprehensive and our setting free from selection issues that may arise when consumers have to opt in to provide their data to some aggregators. Essentially, our data closely resembles data from JP Morgan Chase Institute (e.g., see Ganong and Noel (2019), but for multiple financial institutions rather than exclusively for JP Morgan Chase.

B. *Cryptocurrency and Traditional Investments*

Our research question necessitates identifying cryptocurrency transactions within our bank and credit card data. As mentioned above, the data provider uses advanced analytical tools to identify the name of a (primary and secondary) merchant pertaining to each transaction from the transaction description. For example, if one buys or sells cryptocurrency from a cryptocurrency exchange (e.g., Coinbase), this exchange's name appears in the transaction description and is then picked by machine learning algorithms and included as the 'primary merchant' in the data. In certain cases, a cryptocurrency exchange can be categorized as a secondary merchant, for instance, when the primary merchant is a payment system which channels the funds to the exchange (e.g., payments to eToro through PayPal Crypto Hub).

We exploit this information in the data to identify all account transactions, both debits and credits, involving crypto exchanges and platforms. There are around 43 crypto investing venues in the data, although most of the transactions we observe are ultimately handled by Coinbase, which as of January 2022 routed more than 65% of the transaction volume in the U.S.. Then, we observe when users deposit funds into their crypto wallets and when they withdraw funds from these crypto accounts into their bank account. Because we do not have access to specific token-level data, we do not know the specific cryptocurrencies that are purchased or sold through the external crypto wallet. However, a significant fraction of these transactions contain such information in the description text field and all of these have Bitcoin or Ether as additional information. We therefore assume that most of the transactions we are observing involve these two major cryptocurrencies, although for most of our analysis this is non-consequential as we are more interested about the broader question related to investment in crypto.

To compare cryptocurrency investing with traditional investing, we complement these data by creating similar measures of buying and selling traditional assets based on merchant names in the transaction level data. Specifically, we identify all the major brokerages, such as Charles Schwab and E*Trade, and collect information about debits and credits towards and from these accounts. This procedure allows us to collect information about whether and to what extent households invested in traditional asset classes in an active manner. We also include other large traditional financial institutions, such as Vanguard and Fidelity, providing information about the passive investments, which allows us to better understand the overall investors' positions in traditional markets.

We also use consumption patterns from the transaction data set to create consumer-level characteristics. We create both time-varying characteristics, such as salary income or spending, and time-invariant ones, such as whether a consumer was ever financially constrained (e.g., hand-to-mouth, overdrafter) or is risk-loving (e.g., ever gambled).

Table I presents the basic summary statistics. The average monthly income is about \$6,500, users tend to make about 50% of their transactions online. Total spending is about \$7,000, with about \$600 spent on housing. Credit card spending is on average equal to \$1,800. Furthermore, we find that about 60% of the households in our sample are homeowners. About 33% of individuals incurred at least one overdraft during our sample period. Finally, about 1% of individuals engage in gambling activities, which are identified by analyzing the description text of the transactions.

C. *Stimulus Checks*

We use the information from transaction descriptions for deposits to identify stimulus check payments in our data. It is more straightforward to identify these payments for Stimulus II and III because of designated IRS codes that could be picked up from the transaction descriptions. We identify stimulus payments for Stimulus I from the size of of tax refunds in the bank account and credit card data received starting April 1, 2020. Specifically, we search for IRS tax refund transactions with amounts calculated as $\$1,200 \times a + 500 \times b$, where $a = \{1, 2\}$ is the marital status, 1 denoting single individuals and 2 denoting couples, and $b = \{1, 2, ..., 10\}$ is the number of children in the household. We infer the family composition from second- and third-round stimulus payments to the same individual in our data.

Using this approach, we are able to identify 440,586 first-round stimulus payments, 48,598 second-round stimulus payments, and 17,284 third-round payments. The second round pf stimulus checks (Stimulus II) reached fewer individuals than the first round (Stimulus I), so we should expect a relatively smaller number of treated investors. The third round (Stimulus III) reached the most individuals, but we only observe only around 30% of the program months in our sample, so the number of recipients there should be much smaller than the number for Stimulus I.

D. *Inflation Expectations and Inflation Exposure*

We use three measures of inflation in our last set of tests of the relation between inflation and crypto investing. First, we use the Consumer Price Index for All Urban Consumers (*CPI-U Inflation*) from the Bureau of Labor Statistics (BLS) to compute realized inflation. It is a backward-looking measure of aggregate inflation based on a market basket of consumer goods and services. This monthly measure varies over time, but does not vary across individuals in our sample.

Second, we use the University of Michigan's Surveys of Consumers: Inflation Expectations series (*12-Month E[π]*), which measures the median expected price change over the following 12 months based on surveys of consumers.[6] The main advantage of this measure is that it is a forward-looking estimate, which should matter more for financial choices of individuals than realized inflation. Again, the main drawback of the measure is that it varies only over time (monthly) but not across consumers. The correlation between *CPI-U* and *12-Month E[π]* in our data set is 0.679.

Third, we construct a measure of inflation exposure at the consumer-month level based on price changes of various categories in an individual's consumption basket (*Investor eCPI*). Malmendier and Nagel (2016) find that individuals form their inflation expectations based on their own experience with inflation. Therefore, inflation expectations should be positively correlated with recent inflation exposure. D'Acunto et al. (2021) specifically relate inflation expectations to consumers' exposure to price changes for groceries in their consumption baskets. Weber, Gorodnichenko, and Coibion (2022) show that U.S. consumers' exposure to price changes via their consumption bundles was positively correlated with inflation expectations during the Covid-19 pandemic, especially for some categories of consumers such as lower-income Americans.

We use data on monthly changes in the CPI from 2010 to 2021 from the BLS. The data vary across regions (e.g., Northeast, Midwest, West, and South), categories of expenditures (e.g., fuel, groceries), and time (i.e., months).[7] It is straightforward to map BLS regions to U.S. states in our transaction-level data to calculate changes in the local CPI. Mapping BLS consumption categories to transaction categories in our data requires more work because the categories in the two data sets do not precisely overlap. We thus manually create a crosswalk between these categories. We then compute monthly realized inflation in each consumption category for each individual in our transaction data. Finally, we follow an approach similar to D'Acunto et al. (2021) and aggregate these separate measures of inflation at the individual/month level by weighting price changes for each consumption category using the weights of these categories in each individual's consumption basket over the preceding 12 months.

We focus on consumption bundles rather than all spending bundles to construct our investor-level measure of inflation (i.e., *Investor eCPI (Consumption)*) because consumers observe these price changes most frequently and easily through their shopping behaviour.[8]

[6] See `https://fred.stlouisfed.org/series/MICH`.

[7] The BLS CPI data are available in varying degrees of granularity, and there is a trade-off between geographic aggregation and consumption category specificity. That is, while all consumption categories are available at the national level, only a subset is available at various regional levels. We chose the regional level for CPI data because it maps cleanly to states and has higher granularity than other levels (e.g., the MSA level) in terms of consumption categories. See `https://www.bls.gov/eag`.

[8] The results are robust to using total spending to define weights for inflation exposure calculations.

We measure these consumption baskets ex ante (over the preceding 12 months) because contemporaneous inflation can affect consumption bundles, especially during economic downturns such as Covid-19 (e.g., see Cavallo, 2020). Our measure of inflation exposure has positive but relatively low correlation with *12-Month E[π]* of 0.360.

Specifically, we measure investor-level inflation exposure as follows:

$$\textit{Investor eCPI (Consumption)}_{it} = \frac{\sum_{c=1}^{n}\{\sum_{k=t-12}^{t-1} X_{ick} \times \Delta CPI_{sct}\}}{\sum_{c=1}^{n}\sum_{k=t-12}^{t-1} X_{ick}}, \tag{1}$$

where $\Delta CPI_{sct} = [CPI_{sct}/CPI_{sct-1}]-1$ is the change in the CPI in month t for consumption category c in state s and X_{ict} is the total expenditure for individual i in our transaction data residing in state s in months *t-12* to *t-1* across each consumption category c.

III. Who Invests in Crypto?

The first part of our analysis explores the main characteristics of investors' demand for this new asset class. We take advantage of the granularity of the data and the information related to users' characteristics to provide a detailed picture of who these crypto investors are and the trends around crypto investing.

A. *Crypto Investing Patterns and Investors*

We begin by describing when investors started to participate in the crypto market. One hypothesis is that the interest in this market coincided with the popularity and performance of its major currency, i.e., Bitcoin (BTC). Since inception, the average rolling 12-month return for Bitcoin has been 411%, with a standard deviation of over 1,000%. Large returns might attract new investors as the lottery-like nature of the payoff becomes more evident. Figure 1 plots monthly cryptocurrency investment in our sample and overlays it with statistics about Bitcoin. The plots clearly show that investors allocated significantly more capital to this asset class during the first 2017 boom, when BTC prices went from roughly $2,000 to $14,000. We observe similar dynamics during the latest crypto boom in 2020–2021, when BTC experienced a skyrocketing increase prices from $10,000 to $50,000. This pattern holds both if we look at BTC buy-and-hold returns (Panel A), BTC prices (Panel B), and BTC trading volume (Panel C).

While high returns appear to draw the attention of potential crypto investors, in Figure 2 we find that high returns also lead existing investors withdraw a substantial amount of money from crypto exchanges. In Panel A, we plot crypto withdrawals, while in Panel B we plot net crypto deposits (i.e., deposits - withdrawals) against Bitcoin prices. Similarly to Figure 1, we find that large price spikes are correlated with large amounts of crypto withdrawals, particularly during the first boom in 2017. As a result, net deposits are relatively flat until the second run-up in late 2020, when total deposits substantially outpace withdrawals.

We further examine the withdrawal patterns visible in Figure 2 by zooming in on the large withdrawal spike that occurs in late 2017 after the Bitcoin price first tops $10,000. Are these withdrawals primarily made by early adopters who experienced all of this run-up, or are investors who experienced only a portion of this gain also exiting? Figure 3 plots net deposits to cryptocurrency exchanges in the months surrounding this Bitcoin run-up separately for households that first adopt crypto before 2017 and households that adopt crypto from 2017-2018. The figure clearly shows that it is the early adopters who withdraw money from crypto exchanges following this large price run-up while new adopters are depositing large amounts. A similar pattern is observed during the 2020 price spikes, with households experiencing large gains realize a substantial fraction of them to deploy for consumption and investment in other assets.

To put this investment activity into perspective, we scale the size of the crypto investment for the users we analyze by total debits and total spending. Figure 4 shows that both during the earlier boom and in the latest part of our sample, the crypto investment share has approached its highest historical point, about 3% of total debits and about 6% of total spending.

To test whether the attention garnered by crypto markets during bull periods has resulted in new investors joining the flock, we report the number of new cryptocurrency investors by month in Figure 5. At its peak in 2017–2018, crypto was able to add up to 10 thousand new investors a month within our sample. This number has been significantly lower in the latest boom, where we observe about 5 thousand new investors a month being added to the crypto market in 2021.

Another potentially informative cut of the data is provided by the geographical distribution of the crypto investments. Figure 6 presents state-level maps of the U.S. reporting the growth in crypto investment from 2016 to 2021. We find that the annual change in the probability of investing in crypto over time for the different states in the US. We find that the most active states during the booms, like in 2017 and 2020, are also those we find a decline in the probability of investing in crypto during the downturns, 2018–2019.

We also leverage the nature of our data to explore the distribution of crypto investments in our sample across other key financial characteristics. Figure 7 reports the percentage of investors by income class, as computed in December 2019, for both the count and volume of crypto transactions. Panels A and B report these statistics separately for early and late adopters, defined based on whether their first transaction in crypto is earlier than the 2017 peak. Panel C reports the full sample statistics. Investors earning more than $75k are the most active, with individuals in each bracket making about 20% of the transactions. However, individuals earning less than $45k still make more than 10% of the transactions. In terms of volume, the bulk of the volume is generated by the investors on the right tail of the income distribution, those earning more than $150k. These patterns are similar for both early and late crypto adopters. This evidence suggests that while wealthier investors tend to invest the largest amounts into cryptocurrency, lower income individuals are still sizable participants in the market.

Columns 1–2 of Table I compare the full sample characteristics with crypto users, and Columns 3–4 compare early adopters with late adopters. Columns 5–6 report key statistics differentiating between those who adopted crypto during Covid and those receiving stimulus payments. Column 2 shows that crypto users are more likely to own a house, exhibit higher income and higher total spending compared to the full sample of individuals. They are also more likely to gamble and to be unemployed over our sample period. However, crypto users are less likely to be hand-to-mouth individuals. By focusing on crypto users, we find in Columns 3 and 4 that early adopters are even more likely to gamble than late adopters, incur more overdraft fees, and spend more and a higher fraction of their spending is online than late adopters. Late adopters are more likely to be unemployed and to be hand-to-mouth households.

Table I also shows that crypto adopters have higher incomes than non-adopters: annual salary income is about $3,700 higher for adopters. Some of this difference is likely driven by the fact that early crypto adopters were particularly high income. Figure 8 shows that early adopters also have higher incomes than late adopters; the entire income distribution shifts leftward over time. While crypto adopters have more income than non-adopters, their overall spending patterns are quite similar. Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter (2023) show that there are no substantial differences in the amount of spending on auto, housing, groceries, utilities, or medical expenses. Consistent with their higher income, crypto users do spend a bit more on discretionary items such as entertainment and restaurants.

Our transaction data does not contain demographic information such as race or education. However, for about half of the households in our sample, we can infer the zip code of the household's home residence based on location information contained in the transactions. For this sample, we compare zip code demographic differences.

In Panels A and B of Table II we show the zip code distribution of race and education, respectively, for crypto and non-crypto adopters. On average, late crypto adopters and non-adopters live in zip codes with no meaningful differences in race or education. In contrast, early crypto adopters live in zip codes with a lower percentage of Black population (11.1% vs. 12.1% for non-adopters). Crypto adopters also live in areas with more educated people. For example, crypto adopters live in zip codes where 25.6% of adults have a college degree and 18.3% have a graduate degree, whereas non-adopters live in zip codes where 24.0% and 16.4% have college and graduate degrees.

We next explore differences in zip code size, income, and occupation and report the results in Panels C, D, and E of Table II, respectively. Early crypto adopters live in bigger zip codes; on average the zip code population is about 1,800 people more than zip codes where late- or non-adopters live. The zip codes that early adopters come from are also more wealthy. Median annual household income is about $4,000 higher in early adopter zip codes relative to non-adopter zip codes, likely driven by the fact that there is a higher fraction of people working in managerial or professional occupations. We find no meaningful differences in population, income, or occupation across late-adopter and non-adopter zip codes.

Finally, in Panel F of Table II we summarize industry exposure. At the zip code level, the industry breakdown is nearly identical across early, late, and non-adopters, with the exception that early adopters are more likely to live in zip codes with professional industries.

B. Crypto and Traditional Investments

As a large new asset class, cryptocurrency investment can be one component of a balanced investment portfolio. We thus seek to better understand the extent to which traditional investment activities coexist alongside cryptocurrency investments within a given household and how investment behavior differs across these asset classes. Note that we are looking at post-tax transfers into brokerage accounts, so we are only capturing active contributions and trading by investors, which is indeed more consistent with the crypto investment than 401k automatic contributions.

As a basic comparison, Figure 9 plots the median yearly investment by income class and asset class (i.e., crypto versus traditional assets). We find that for most users, those earning less than $75k, their investments in the crypto market and in traditional markets are quite comparable. These investments tend to be small, less than $1,000, but the crypto amounts track the traditional ones closely. More significant divergences occur for the wealthier individuals, for whom crypto investment tends to be a relatively smaller component of overall investments. For those earning between $100k and $150k, the crypto investment represents about half of their traditional investments. The gap increases for those earning more than $150k, who tend to invest about three times more in stocks and bond than in crypto.

Another way of looking at crypto investing patterns by income is to note that crypto investments account for about half of observable post-tax investment for low-income investors and under 25% for wealthier ones. Similarly, lower income households spend a much higher fraction of their salaries on crypto investment. Consistently over our sample period we find that the least wealthy investors allocate up to 10% of their salaries to cryptocurrency investment.

In Figure 10, we plot the distribution of crypto portfolio values over time. We estimate the value of crypto wealth by assuming that investors purchase a basket of Bitcoin and Ethereum on the day that they deposit money to a crypto exchange (weighted by that day's relative market cap). We then grow this portfolio by the return on these two coins.[9] Perhaps unsurprisingly given the rise in crypto prices, the figure shows that the aggregate distribution of crypto portfolio values has shifted right over time.

As crypto investors' portfolios grow, they might begin to rely on crypto as their primary source of savings. In this case, investment in crypto assets might crowd-out out investment in more traditional assets. Figure 11 shows that this is likely not the case. Overall, we find that crypto investors tend to invest very similar amounts in traditional assets as non-cryptocurrency investors do at every income level.

C. *Bitcoin Returns and Crypto Investing*

We complement the previous analysis by looking at deposits to and withdrawals from cryptocurrency accounts in relation to market conditions. Specifically, we investigate to what extent investors are more willing to invest or withdraw funds from the crypto market in response to changes in Bitcoin (BTC) prices. We estimate a specification with the main dependent variables being changes in debits, credits, and net flow on BTC contemporaneous and lagged returns. These tests are at the monthly level and make use of time-series variation in the data. We estimate the following autoregressive AR(1) model:

$$\Delta y_t = \alpha_0 + \alpha_1 BTC\ Return_t + \alpha_2 BTC\ Return_{t-1} + \varepsilon_t, \tag{2}$$

where Δy_t represents the dollar amount of change in crypto deposits, withdrawals, or net flows. $BTC\ Return_t$ is the contemporaneous Bitcoin return measured in percent and $BTC\ Return_{t-1}$ is the lagged Bitcoin return measured in percent. We use robust standard errors.

We report the results in Table III. We observe a significant and positive relationship

[9] Results are similar if we assume investors only purchase Bitcoin, or if we assume they purchase a trading volume-weighted basket of the top 30 coins.

between both investment and withdrawal with respect to Bitcoin prices, with a higher sensitivity of changes in credit, suggesting that overall bullish and bearish market sentiment are a significant factor in driving crypto investment. Column 3 shows that overall net flows are not significantly correlated with lag BTC returns.

Table IV performs a similar analysis for traditional investment and its relation with the S&P 500. We do not find any significant relationship between overall market conditions and investments or withdrawals in traditional markets. This seems to suggest that the active investors in our sample more closely monitor the crypto market when deciding whether to make or withdraw their crypto investments while equity market investments are more consistent across market conditions.

IV. Stimulus Checks and Crypto Investing

A. *Stimulus Checks as Fiscal Response to Covid-19*

The significant spike in crypto sector investments in early 2020, which we document in the previous section, coincided with unprecedented policy response to the Covid-19 pandemic. One of the most significant interventions to curb the adverse effects of the pandemic on the economy was the payment of stimulus checks to millions of U.S. households.

A key feature of these Covid-related stimulus policies was their indiscriminate nature in terms of the actual need. That is, taxpayers received stimulus money regardless of whether they were experiencing financial hardship. The funds were paid in three separate checks: the first one in April 2020 (Stimulus I), the second one in December 2020 (Stimulus II), and the last in March 2021 (Stimulus III). The amounts were $1,200 per adult for the first round, $600 per adult for the second, and $1,400 per adult for the third. In all cases, this aid started phasing out at $75,000 for single individuals and $150,000 for couples.

Given the size of the fiscal stimulus and the fact that even households not suffering from the economic consequences of the pandemic received it, it is possible that a large fraction of these funds ended up being saved and invested, potentially in riskier assets, rather than spent to support the households' finances and the economy as intended (i.e., through consumption). We test this hypothesis by identifying consumers who receive the stimulus payments and tracking their investments before and after these additional funds are received.

B. *Crypto versus Traditional Investing around Stimulus Payments*

We first graphically examine crypto investments relative to the stimulus date in an event study framework, differentiating between the three different stimulus rounds. We measure crypto investments in two different ways. We first consider the probability of crypto investing as a measure of the extent to which the stimulus checks have increased the propensity to invest in crypto on the extensive margin. We then examine the dollar values of crypto investments. We also compare the response of crypto investments following stimulus checks relative to how traditional investments respond to these checks.

We use the staggered timing of the arrival of stimulus payments in retail investors' bank accounts as a source of quasi-exogenous variation in credits available for investing. We compare retail investors to their own selves at a point in the past, in the same calendar week of the year as the stimulus check payment, to have a more precise counterfactual. This comparison allows us to make use of within-investor variation in investing and to account for clustering of stimulus payments around certain calendar weeks in the data. Specifically, we estimate the following regression at the calendar week level:

$$y_{it} = \alpha_{it} + \sum_{k=-6}^{6} \beta_k \mathbb{1}\{Stimulus - t = k\} \times T_{it} + \varepsilon_{it}, \tag{3}$$

where y_{it} represents the likelihood of investing in crypto or traditional asset classes in one specification and the natural logarithm of the dollar amount invested in crypto or traditional assets in another specification. $T_{it} = 1$ for the $+/-6$ week window around the receipt of a stimulus check payment and $T_{it} = 0$ for a random $+/-6$ week period in the past, before the stimulus check payment, for a given retail investor.

We include investor and city/state of residence by income class by week fixed effects α_{it} to absorb not only time-invariant heterogeneity in retail investing by retail investors in our data, but also calendar time (i.e., weekly) effects that vary by income class within city of residence of retail investors. Of note, since investors in our data move across geographies and income classes over time, this specification is more stringent than a specification with only investor fixed effects. It is also more stringent than a specification with only city by income class by week fixed effects because it controls for time-invariant characteristics of the investors, such as their appetite for risk.

We plot the coefficients of interest β_k from Equation (3) estimated for Stimulus I, along with 95% confidence intervals around them, in Figure 12. The top left panel shows a statistically significant spike in the likelihood of investing in crypto in the week of stimulus payment, suggesting that a portion of the financial aid provided by the government was invested in crypto.[10] This increase in the likelihood of crypto investing is maintained in the following six weeks after the payment date. The magnitude of the increase is around 0.005

[10]This result is consistent with survey evidence in Coibion, Gorodnichenko, and Weber (2020) who find that consumers mostly saved their stimulus money or paid down debts from these transfers.

percentage points (pp) per week, or 0.035 pp over seven weeks, which is sizable relative to the generally relatively low likelihood of crypto investing in other weeks. Specifically, we find that the likelihood of making a crypto debit increases by around 20% relative to the mean after the first stimulus payment.

Likewise, we observe a sharp increase in the log dollar amount of crypto investment during the stimulus week in the top right panel of Figure 12. We also find that this higher level of crypto investment in dollar terms is maintained for six weeks after the stimulus checks were disbursed. The economic magnitude is, however, smaller than for the investment propensity. We find that the amount of crypto deposits increased by around 2% in dollar terms after the first stimulus check. It is noteworthy that we see no statistically distinguishable run-up in crypto investing before the stimulus week for either the likelihood of the dollar amount invested for Stimulus I. The absence of pre-trends gives us comfort in interpreting the relation between stimulus payments and crypto investing as likely causal.

One question is whether the crypto investment reacts differently to the stimulus checks than the traditional investments do. We plot the coefficients from the event study analysis of traditional investments for the first stimulus round (Stimulus I) in the bottom two panels of Figure 12. We find a similar spike in the likelihood and the dollar amount of traditional investment in the stimulus week. However, as opposed to crypto investing, the increase in the dollar amounts invested in traditional assets halves already starting from the first week following the stimulus week. Furthermore, the magnitude of the increase in traditional investing around the stimulus payments is significantly smaller than the increase observed for crypto investments, when compared to the mean likelihood and mean dollar amount of traditional investments. These findings corroborate the hypothesis that the additional liquidity provided by the Covid-related fiscal measures such as stimulus checks flew into riskier asset classes like crypto.

We reproduce plots in Figure 12 for the other two rounds of stimulus checks in Figure 13 (Stimulus II) and Figure 14 (Stimulus III). The effects on crypto investing are less pronounced for the subsequent two rounds of stimulus (see top panels of both figures). Although the magnitude of the initial spikes in the stimulus weeks for these rounds are larger than the respective spike for Stimulus I, the levels rapidly drop in the weeks after the stimulus payments. These results suggest that while the first round of stimulus check payments may have had a more lasting effect on crypto investing by retail investors (e.g., by attracting new investors to crypto), the effects of the following rounds are largely transitory (e.g., by providing extra liquidity for outright investing).

The response of traditional investing to the second and third rounds of stimulus payments seems to follow a similar pattern of a spike followed by a gradual decline. The spike for traditional investments during the second round happens one week after the stimulus week, which suggests that retail investors might favor investing excess liquidity in the crypto market before considering traditional asset classes (see bottom panels of Figure 13).[11]

C. Marginal Propensity to Invest (MPI) in Crypto and Traditional Assets

We proceed by formally estimating the marginal propensity to invest (MPI) in cryptocurrencies versus traditional asset classes. We adopt an approach similar to the one in Ganong and Noel (2019) who estimate the marginal propensity to consume (MPC) from unemployment insurance benefits using high-frequency bank account data. We use the stimulus check payments schedule as a source of quasi-exogenous variation in credits of funds to retail investors' bank accounts. Specifically, we estimate the following instrumental variables (IV) specification with the two-stage least squares (2SLS) procedure:

$$x_{it} = \alpha_{it} + \beta \, Post_t + \epsilon_{it} \tag{4a}$$

$$y_{it} = \gamma_{it} + \beta_{\text{MPI}} \, \widehat{x_{it}} + \varepsilon_{it} \tag{4b}$$

where y_{it} represents the dollar amount of investment in crypto or traditional assets and x_{it} is the total credits of funds to an investor i's bank accounts at time t. We instrument x_{it} with the $Post_t$ indicator, which is equal to one for the 6-week period after stimulus and equal to zero for the 6-week period prior to the stimulus. Equation (4a) is the first stage of the 2SLS system and Equation (4b) is the second stage. As in Equation (3), we include investor and city/state of residence by income class by week fixed effects in both stages (i.e., α_{it} in the first stage and γ_{it} in the second stage). This stringent specification absorbs time-invariant differences across investors, such as differences in risk aversion, as well as time-varying trends, including differences in the investment propensity of investors with different incomes or residing in different areas across time and market-wide indicators such as Bitcoin prices. We cluster standard errors at the investor level.

Column 1 of Table V reports the results of the MPI analysis for the entire sample of cryptocurrency investors. The left-hand-side variable is the dollar amount of crypto investment in Panel A and the dollar amount of traditional investment in Panel B. We find positive and statistically significant MPIs for both of these asset classes, although the results for traditional investments are statistically weaker. Across all three stimulus rounds, consumers invest \$5.09 in crypto and \$8.23 in traditional assets for every \$1,000 of stimulus check pay-

[11] We also observe some run-up in transitional investments leading to the stimulus payments in the third round (see bottom panels of Figure 14). Likewise, traditional investment slightly increased before the first stimulus. We are not aware of what may have caused these run-ups.

ments. On average, on exogenous income shock leads cryptocurrency investors to increase investment in both crypto and traditional assets, but the effect is roughly 60% larger for traditional assets.

We recognize that results based on the entire sample of cryptocurrency investors may mask important differences across investor-type. In columns 2–7 of Table V, we explore the effect of investor heterogeneity on MPIs by interacting income with indicators for various investor characteristics. We continue to use the 2SLS framework described above.[12] We first explore the extent to which prior experience with crypto investing matters using an indicator for early adopters in Column 2. We find larger and statistically significant MPIs for both crypto and traditional investments for less experienced investors (i.e., the coefficient on early adopters is negative). On net early adopters, who have more experience with crypto investments, actually slightly decrease their investment in crypto following the income shock, and increase investment in traditional assets by about \$5.9 in the response to every \$1,000 of stimulus check payments.

It is likely that risk-loving investors are more likely to channel their stimulus money to investments in riskier asset classes. It may also be the case that certain types of investors (e.g., more financially constrained ones) benefit more from obtaining extra liquidity from stimulus checks, which allows them to increase discretionary spending and investments in crypto. We explore these possibilities with indicators for four subgroups of investors: (1) crypto investors who gamble at least once in the sample (*Gambler*), (2) crypto investors who tend to consume most of their income (*Hand-to-Mouth*), (3) crypto investors who incur overdraft fees at least once in our sample (*Overdrafter*), and (4) unemployed individuals (*Unemployed*). Columns 3–6 of Table V report the interaction effects on the respective MPI estimates. Relative to non-gamblers, gamblers have an MPI that is about 40% higher for crypto, and nearly 80% higher for traditional investment. This suggests that risk preferences play a role in the decision to invest. We find limited evidence that financial constraints matter for investment decisions following stimulus payments. Hand-to-mouth investors are significantly more likely to invest in cryptocurrency following the income shock, but there is no relation between overdrafts or unemployment and investment. [13]

We complement the above analysis by looking at the heterogeneity in the response to the

[12] We use both the *Post*-indicator and the *Post*-indicator interacted with the characteristic as instruments in these regressions.

[13] In unreported analyses, we also consider income, but find no differences in MPIs across income classes. It is ambiguous whether one should expect any differences between income classes. On the one hand, the stimulus starts phasing out above \$75k and \$150k for single individuals and couples respectively, which could weaken the link between stimulus payments and investments for higher-income investors. On the other hand, the link may be more pronounced for higher-income individuals because of the discretionary nature of crypto investment for these investors.

stimulus check by the timing of initial crypto investing in Table V Column 7. We interact our MPI estimates with an indicator for individuals that first invested in crypto during the Covid period (*Covid Adopter*). After controlling for covid adopters, the overall MPI in crypto is small, negative, and insignificant. In contrast, the estimate on the interaction with *Covid Adopter* is large and very significant. The relation between MPIs in traditional assets and covid crypto adopters is largely similar, suggesting that stimulus checks may have motivated new investors to invest in both crypto and traditional assets, consistent with the increase in the number of new crypto investors in 2020–2021 reported in Figure 5.

We further examine each stimulus round individually and report the results in the online appendix.[14] The overall MPI in crypto increases across each of the three rounds of stimulus. While there are some differences across the interactions, the overall message is broadly the same—stimulus checks provided during the Covid pandemic allowed individuals to invest in both crypto and traditional assets, and individuals with a proclivity for risk-taking were particularly likely to use stimulus money for these investments.

V. Inflation and Crypto Investing

In this Section, we explore how consumer expectations about rising inflation interact with retail cryptocurrency investing. We also examine the heterogeneity of crypto and traditional investing responses to inflation based on investor sophistication, experience, and constraints.

A. Crypto Investing during Rising Inflation: What to Expect?

Inflation started to rise rapidly in the U.S. in 2021. The Consumer Price Index for All Urban Consumers (CPI-U) rose 7.0% over the year, constituting the largest 12-month increase in inflation since June 1982.[15] This dramatic increase in CPI-U resulted in significant and ongoing concerns about the impact of the rising inflation on consumers. It also revived the debate around whether consumers consider cryptocurrencies, especially Bitcoin, as a "digital gold" or an alternative way to hedge against macroeconomic risks such as fluctuations

[14]Table IA.I and Table IA.II reports the results of the MPI analysis for cryptocurrency and traditional investment following Stimulus I, Table IA.III and Table IA.IV show the results of similar analyses for Stimulus II, and Table IA.V and Table IA.VI present the results for Stimulus III.

[15]Several factors contributed to this recent surge in inflation, including unprecedented fiscal measures adopted during the Covid-19 pandemic, pandemic-related supply chain disruptions, and improved labor market conditions. See *Consumer Price Index – December 2021*, BLS News Release, January 12, 2022 at `https://www.bls.gov/bls/news-release/cpi.htm` and *Exploring Price Increases in 2021 and Previous Periods of Inflation* by Edwin Bennion, Trevor Bergqvist, Kevin M. Camp, Joseph Kowal, and David Mead, BLS Beyond the Numbers Vol. 11, No. 7, October 28, 2022 at `https://www.bls.gov/opub/btn/volume-11/exploring-price-increases-in-2021-and-previous-periods-of-inflation.htm`.

in traditional sectors of the economy, sovereign debt default risk, and spikes in inflation.[16]

There is disagreement in the literature as to the effects of inflation on retail investors' demand for financial instruments. For example, Kanz, Perez-Truglia, and Galashin (2022) find evidence that higher inflation expectations increase demand for inflation-indexed securities, consistent with hedging motives. By contrast, Braggion, von Meyerinck, and Schaub (2022) find that retail investors, especially less sophisticated ones, buy less and sell more stocks when they face higher local inflation, consistent with money illusion. It is unclear which of these theoretical concepts, if any, are applicable to cryptocurrencies.

On the one hand, cryptocurrencies as financial assets do not have cash flows or dividends, which can grow with inflation and hence provide a hedge. Thus, one could expect rational investors to *sell* cryptocurrencies in response to expectations of future inflation, in order to satisfy their consumption needs or to buy other securities, which produce cash flows that can provide that hedge (e.g., stocks). Additionally, expectations of future inflation might increase retail investor risk aversion, inducing them to sell risky assets such as cryptocurrencies, which are very volatile, and buy safer traditional assets such as gold or government bonds (i.e., "flight to quality" as in Caballero and Krishnamurthy, 2008).

On the other hand, cryptocurrencies may grow with demand faster than traditional assets, especially when investors pursue momentum strategies (e.g., Kogan, Makarov, Niessner, and Schoar, 2022), bet on wider adoption of blockchain technology or cryptocurrencies as means of payment (e.g., Biais, Bisiere, Bouvard, Casamatta, and Menkveld, 2023), or perceive crypto as a safer asset than dollars or a more liquid asset than traditional securities. For example, consumers may exhibit "flight to safety" behavior during periods of high inflation (e.g., Barsky, 1986; Baele, Bekaert, Inghelbrecht, and Wei, 2020) and reallocate financial assets toward cryptocurrrencies given the pre-determined nature of crypto supply programmed in the underlying blockchain protocols.[17] Similarly, due to high liquidity of major cryptocurrencies such as Bitcoin, consumers may reallocate their less liquid financial assets toward crypto during high uncertainty due to "flight to liquidity" (e.g., Vayanos, 2004; Brunnermeier and Pedersen, 2009). In this case, one should expect rational investors to *buy* cryptocurrencies in greater quantities if they expect future inflation increases.

Additionally, if retail investors are not fully rational, they may make valuation mistakes.

[16]See for instance `https://www.forbes.com/sites/forbesfinancecouncil/2020/05/11/is-bitcoin-really-digital-gold` and `https://www.bloomberg.com/news/articles/2023-05-15/debt-ceiling-negotiations-have-investors-eyeing-gold-if-us-defaults`. Scarcity and finite supply are thought to be the most important similarities between cryptocurrencies and gold from the perspective of their hedging potential.

[17]For example, Bitcoin has a steady supply growth rate with new BTC emitted through block rewards approximately every 10 minutes. The block reward (currently at 6.25 BTC) halves every 210,000 blocks, i.e., approximately every four years. This schedule means that BTC growth rate is stable in the short-run.

For example, individuals may not understand that cryptocurrencies are not backed by real assets and do not produce cash flows and may thus buy these assets during periods of rising inflation because of valuation errors. This behaviour should be especially pronounced for certain types of investors such as less sophisticated retail investors.

Ultimately, how cryptocurrency investments respond to inflation expectations is an empirical question. Addressing this question requires detailed data on individual-level inflation expectations and investing patters. It is also challenging to empirically detect the effect of inflation on individual investment decisions during periods of low or stable inflation because retail investors can be slow to incorporate their inflation expectations into discount rates when inflation is low (e.g., Katz, Lustig, and Nielsen, 2017) or because they may exhibit rational inattention when inflation stabilizes and marginal returns to accurately estimating inflation are low (e.g., Sims, 2003). Our detailed transaction data allow us to examine the extent to which expected changes in prices impact investors' propensity to allocate a portion of their portfolios to crypto, especially in a period of high and rising inflation.

B. *Investment Response to Realized, Expected, and Investor-Level Inflation*

We start by exploring the relation between crypto investing and our three measures of inflation: aggregate realized inflation (*CPI-U Inflation*), future 12-month inflation expectations (*12-Month E[π]*), and investor-level inflation exposure (*Investor eCPI (Consumption)*). We report the baseline results in Table VI, Panel A, for our sample of crypto users.

Columns 1 and 4 report the results of regressing crypto investments on a measure realized inflation (CPI-U). We control for investor and state by income class fixed effects but not for time fixed effects because this measure only varies over time. We find that increases in CPI-U inflation are positively related to the likelihood of making a crypto investment (Column 1) and the dollar amount of crypto investment (Column 4). The magnitude is economically significant. A one percentage point (pp) increase in CPI-U inflation is associated with a 2.54 pp increase in the likelihood of consumers making a crypto investment in a given month, or a 59.1% increase relative to the sample mean of 4.29 pp. It is also associated with an increase in the dollar amount of crypto investment by an average of $10.80, or a 15.8% increase relative to the sample mean of $68.3.

The effect of aggregate 12-month inflation expectations (forward-looking) on crypto investing is similar. A one percentage point (pp) increase in 12-Month E[π] is associated with a 2.63 pp increase in the likelihood of consumers making a crypto investment (Column 2) and a $10.96 increase in the dollar amount of crypto investment (Column 5). These results are broadly consistent with Giglio et al. (2020) who show that retail investors' beliefs are incorporated in their asset allocation decisions in the stock market.

We proceed by investigating whether an individual's own experience with inflation is related to crypto investing. As described above, we construct a time-varying investor-level measure of inflation exposure by weighting regional price changes for specific types of goods and services by their share in the individual's consumption basket. The idea is that depending on an individuals' consumption patterns, inflation might be perceived in a significantly different way. For example, individuals that have a basket of consumption goods where gas and groceries are the largest categories, which experienced particularly high price increase and which cannot be easily adjusted in response to inflation, may be more concerned with rising price levels and thus more inclined to search for inflation hedges. Empirically, individual-level inflation exposure allows us to conduct within-investor tests while controlling for time trends, including time-varying local economic factors, which could be correlated with crypto investing.

We present the results of regressing crypto investing variables on this consumption-based inflation measure in Columns 3 and 6 of Table VI, for our sample of crypto users. We include a set of investor and state by income class by month fixed effects in these regressions. Even in this case, we find a significant reaction of crypto investment to individual-level inflation exposure. A one percentage point (pp) increase in Investor eCPI (Consumption) is associated with a 0.8 pp increase in the likelihood of consumers making a crypto investment (Column 3), or a 18.7% increase relative to the sample mean. It is also associated with a $2.39 increase in the dollar amount of crypto investment, or a 3.5% increase relative to the sample mean (Column 6).

It is useful to compare the response of crypto investments to inflation to that if traditional investments, for the same group of individuals who invest in crypto (to avoid selection concerns). We thus examine the response of traditional investments to our measures of realized, expected, and investor-level inflation in Table VI, Panel B. We find mixed results. The coefficients of CPI-U inflation are positive and statistically significant in Columns 1 and 4, consistent with the results on crypto investing. The magnitudes of the effects are also similar. At the same time, the coefficients of 12-month inflation expectations are negative and statistically significant in Columns 2 and 5. Investor-level inflation exposure is positively related to the probability of making a traditional investment in a given month but is not significantly related to the dollar amount of traditional investment (the coefficient is negative).

We further focus on the investor-level inflation exposure measure (*Investor eCPI*) as the most stringent measure empirically, which allows for the variation across investors in the presence of time fixed effects. We examine heterogeneity in the effects we find next.

C. *Heterogeneous Response of Crypto and Traditional Investing to Inflation*

The effects of inflation on cryptocurrency investing are likely heterogeneous. We thus examine heterogeneous response of crypto to inflation based on several measures of financial sophistication, risk attitude, and crypto investing experience. Panel A of Table VII reports the results of interacting our measure of consumption-based inflation exposure (*Investor eCPI (Consumption)*) with proxies for these investor traits. Of note, the coefficients of the level of *Investor eCPI (Consumption)* remain positive and significant in three out of four specifications after we include these interactions.

We study heterogeneity by investor sophistication in Table VII, Column 1. Increased levels of financial sophistication could lead to increased awareness of the hedging properties inherent in cryptocurrency relative to say stocks or bonds (of lack of such properties) and the availability of other tools to hedge inflation. We identify more sophisticated investors by flagging those who work for the top 200 finance firms, which account for 99% of the securities trades debit transactions in the data. We define a sophisticated investor as an investor who has ever received any salary income from one of these finance firms. Based on this definition, 1.1% of consumers in the data are financially sophisticated versus 7.0% of crypto investors. Although not a perfect measure, we believe that working for a large financial institution is likely to be correlated with sophistication due to one's background (e.g., education) and work experiences. The results in Column 1 of Table VII indicate that sophisticated investors are much more responsive to inflation expectations than non-sophisticated ones are. Importantly, we include income fixed effects in this specification to isolate the effect of sophistication and account for wealthier investors likely being also more financially sophisticated.

Column 2 of Table VII reports the results for gamblers. We identify gamblers as consumers who ever transacted at casinos, lottery kiosks, play centers, or betting websites. Consumers who gamble are likely more risk loving and may thus be more comfortable investing in high-risk assets such as crypto during periods of economic uncertainty. Additionally, gamblers may pursue hedging strategies more aggressively. The coefficient of the interaction term is again positive and statistically significant (Column 2), suggesting that gamblers invest more in cryptocurrencies when their inflation exposure increases.

We now turn to two measures of retail investors' experience with the crypto market. Table VII, Column 3 interacts inflation exposure with a dummy for investing in crypto prior to January 2018 (*Early Adopter*). These investors personally experienced the run-up and the collapse in Bitcoin price in December 2017.[18] We find that early adopters of crypto invest significantly less in crypto when their inflation exposure increases. One interpretation

[18] Aiello et al. (2023) examine this run-up and the resulting crypto wealth effects in greater detail.

of this result is that the 2017 Bitcoin market collapse could have altered these investors' risk attitudes toward the crypto market and they became less likely to invest in risky assets such as cryptocurrencies during periods of macroeconomic turmoil, consistent with the intuition in Malmendier and Nagel (2011). Adding the coefficient of the level and the interaction term results in a negative sum ($7.842 - 13.09 = -5.248$), suggesting withdrawal of money from the crypto market by early investors with rising inflation exposure.[19] Finally, Column 4 reports the results for heterogeneity based on a dummy for consumers who invested in crypto for the first time in January 2020 or later (*Covid Adopter*). We find a positive and statistically significant coefficient of the interaction term with an insignificant coefficient of the level, suggesting that most of the effect comes from consumers who adopted crypto during the Covid-related economic downturn and subsequent rise in inflation.

Panel B of Table VII reports similar results for the dollar amount of traditional investments as the dependent variable. We first note that the coefficient of the level of inflation exposure is negative and statistically significant in three out of four specifications. Therefore, an average *crypto* investor is less likely to invest in traditional securities such as stocks and bonds when inflation increases. While this result is consistent with Braggion et al. (2022), it is less likely due to money illusion because the sample consists with the same individuals who increase their investments in crypto when being more exposed to inflation (see Panel A of Table VII). Rather, it is more consistent with an average crypto investor re-balancing their investment portfolio away from stocks toward crypto when inflation rises. The interaction terms load similarly to those in Panel A of Table VII.

The results in Table VIII reveal heterogeneity in the effect across retail investors by the severity of their budget constraints. Column 1 of Panel A examines whether the effect of inflation expectations on crypto investment differs by investor income. If cryptocurrency is perceived to be a reliable inflation hedge and if income is a proxy for wealth, those with greater income likely have higher financial wealth and a greater incentive to hedge against inflation fluctuations. Hence we would expect to see that increases in inflation expectations lead to larger increases in cryptocurrency deposits for higher-income investors. On the other hand, if cryptocurrency is perceived to be a reliable inflation hedge and if income is a proxy for financial constraints, we would expect increases in inflation to lead to larger increases in cryptocurrency deposits for lower income investors. Table VIII, Column 1 shows that crypto investments are more sensitive to inflation expectations for consumers with below-median income. This indicates that the low-income earners increase their crypto investments more in response to increases in inflation expectations, perhaps due to the

[19] Of note, this likely is not a time-series effect because we include time fixed effects in the respective specification.

higher salience of inflation for these individuals due to insufficient slack in their budgets to cover higher prices. Consistent with this hypothesis, we document in Column 2 that higher variability in salary income is positively related to crypto investing (positive and significant coefficient of *Salary Volatility*), and even more so when inflation exposure is high. We also find greater sensitivity of crypto investments to investor-level inflation for two specific proxies for financial constraints—being a hand-to-mouth consumer and an overdrafter. Interestingly, we find a negative effect of being unemployed on the relation between expected inflation and cryptocurrency investing.

Similarly to Table VII, Panel B of Table VIII examines heterogeneity in the effects of investor-level inflation exposure on traditional investments, by our measures of budget constraints. We find evidence of traditional investments responding more positively to inflation exposure for low-income investors, those with higher salary income volatility, and hand-to-mouth consumers. By contrast, overdrafters and unemployed individuals are more likely to decrease their traditional investments in response to inflation. Overall, our findings suggest that investors, especially sophisticated and low-income ones, likely consider cryptocurrencies as an inflation hedge, even more so than traditional securities such as stocks and bonds.

VI. Conclusion

This paper provides the first comprehensive description of crypto investors and what motivates them to invest in crypto. Rather than using on-chain data, which only provide anonymous information about wallet addresses, we exploit detailed bank account information for a representative sample of U.S. consumers, which offer information about deposits to and withdrawals from crypto accounts at centralized exchanges like Coinbase. We exploit the fact that we observe a detailed picture of the investors' finances to investigate the relation between traditional and crypto investments to BTC appreciation, fiscal stimulus, and inflation.

We start by examining the characteristics of crypto investors and the evolution of retail crypto investing. We document significant interest by retail investors in crypto during booms in Bitcoin prices and returns in 2017 and 2020–2021. We also show that wealthier individuals are more likely to invest in the crypto market, especially among early crypto adopters. We also relate crypto investing to the Bitcoin returns over time. We show that investors' deposits to and withdrawals from the crypto exchanges are positively and significantly correlated with BTC returns. This relation is in contrast to what we observe for traditional investment, where investors do not seem to realize gains when market conditions improve. This evidence also suggests that the increase in crypto prices might resemble the dynamics of a bubble.

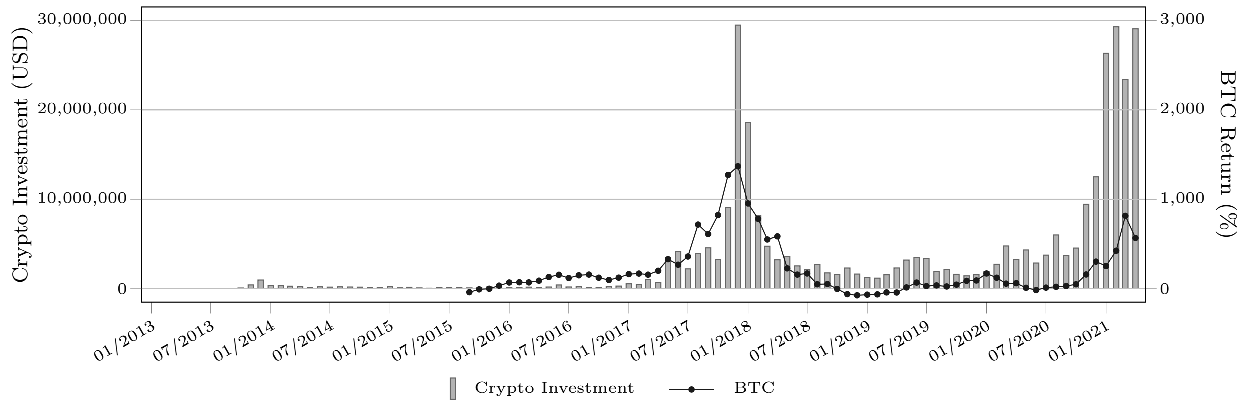
We next examine several potential drivers of crypto investing. First, we examine whether fiscal measures adopted during the pandemic, such as stimulus check payments, can explain the increase in interest in the crypto market. While we find that investors did invest a fraction of their stimulus checks into crypto, these amounts totaled only a small portion of overall crypto investment in recent years. We find evidence consistent with individuals who are more financially constrained (e.g., overdrafters, had-to-mouth investors) turning to the crypto market as a potential additional investment. The sizable amount and discretionary nature of stimulus payments may have somewhat relieved the constraints for these consumers, allowing them to invest these additional payments in a risky asset like crypto.

Second, we provide evidence that inflation expectations are positively correlated with crypto investing, in the time series. We then construct a measure of consumer-level exposure to inflation, based on their consumption baskets. We show that investors who are more exposed to inflation are more likely to invest in crypto. This relation is stronger among more financially sophisticated investors, providing some evidence that crypto may be seen as one potential hedge against the rise of inflation.

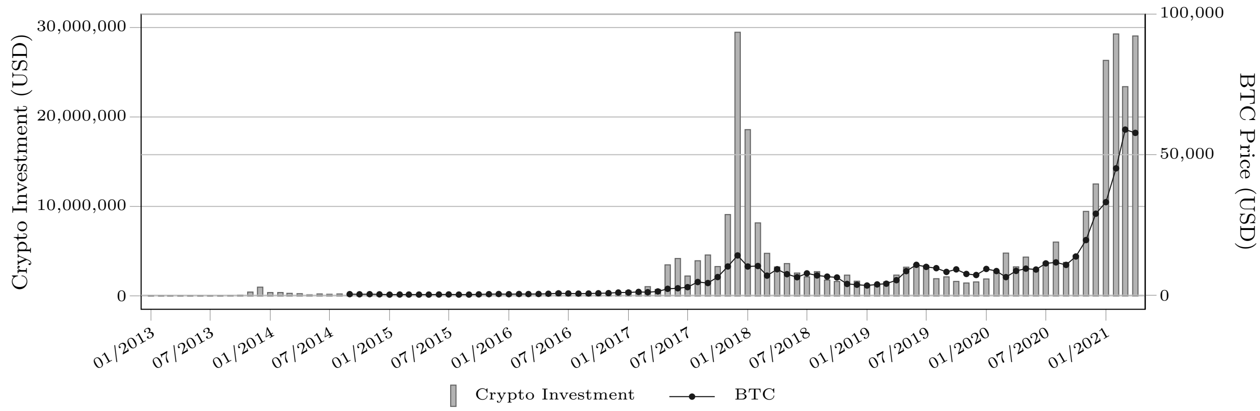
Our results point to a link between government interventions – such as fiscal and monetary policies – and investing in risky asset classes like cryptocurrencies.

Figure 1. Crypto Investment and BTC Dynamics

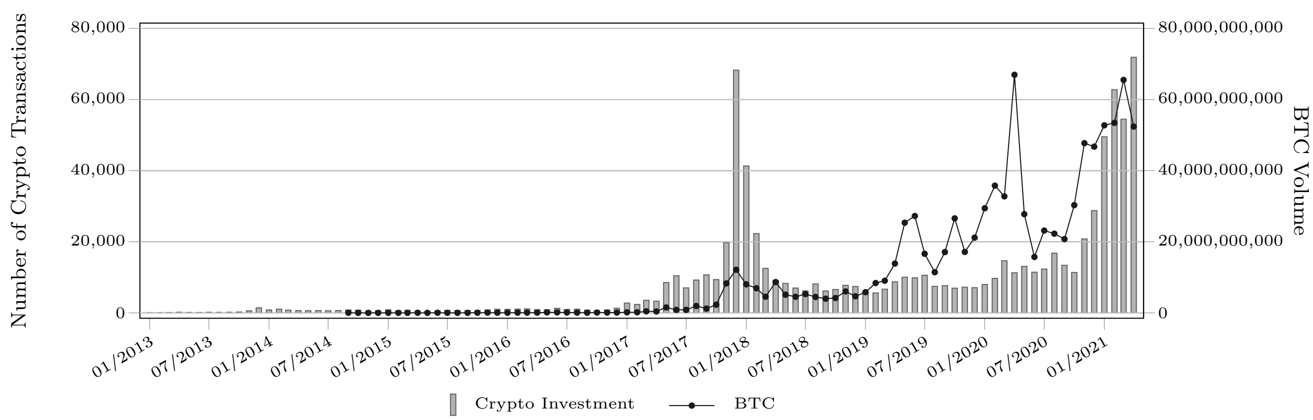
Panel A: Monthly Cryptocurrency Investment ($) and BTC Return (%)



Panel B: Monthly Cryptocurrency Investment ($) and BTC Price ($)



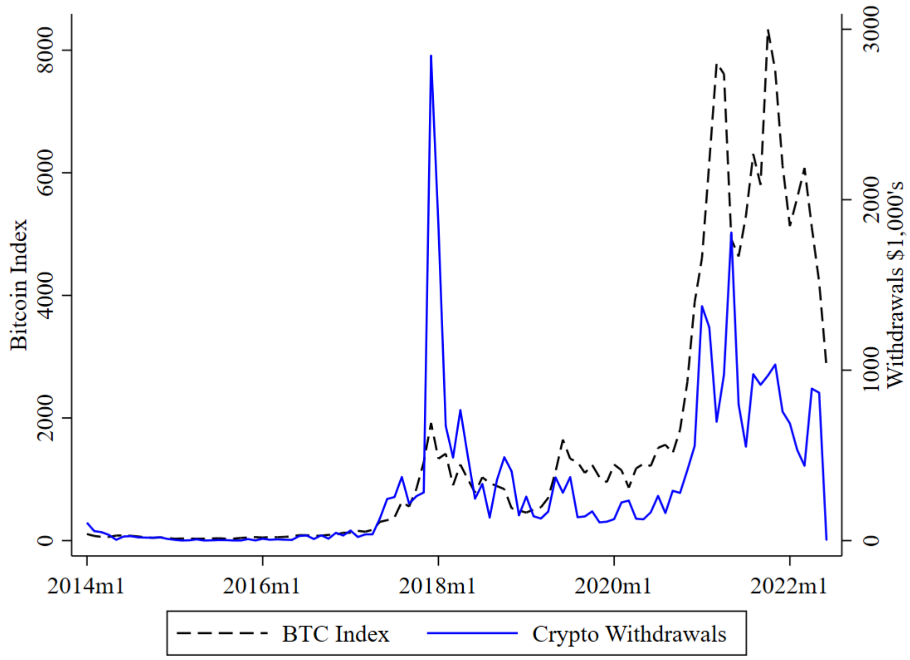
Panel C: Monthly Cryptocurrency Investment Transactions and BTC Volume



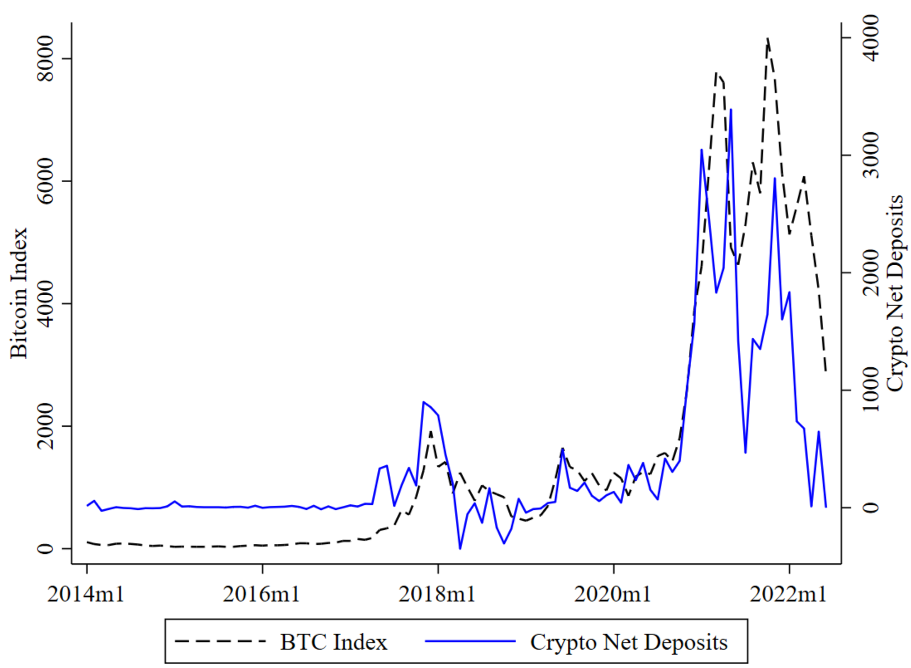
The figure above displays the relationship between cryptocurrency retail investment flows and BTC dynamics. Panel A plots monthly dollar cryptocurrency investment amount vis-à-vis BTC returns. Panel B plots monthly dollar cryptocurrency investment amount vis-à-vis BTC price. Panel C plots the number of cryptocurrency investment transactions vis-à-vis BTC volumes.

Figure 2. Crypto Prices and Crypto Portfolio Activity

Panel A: Crypto Withdrawals

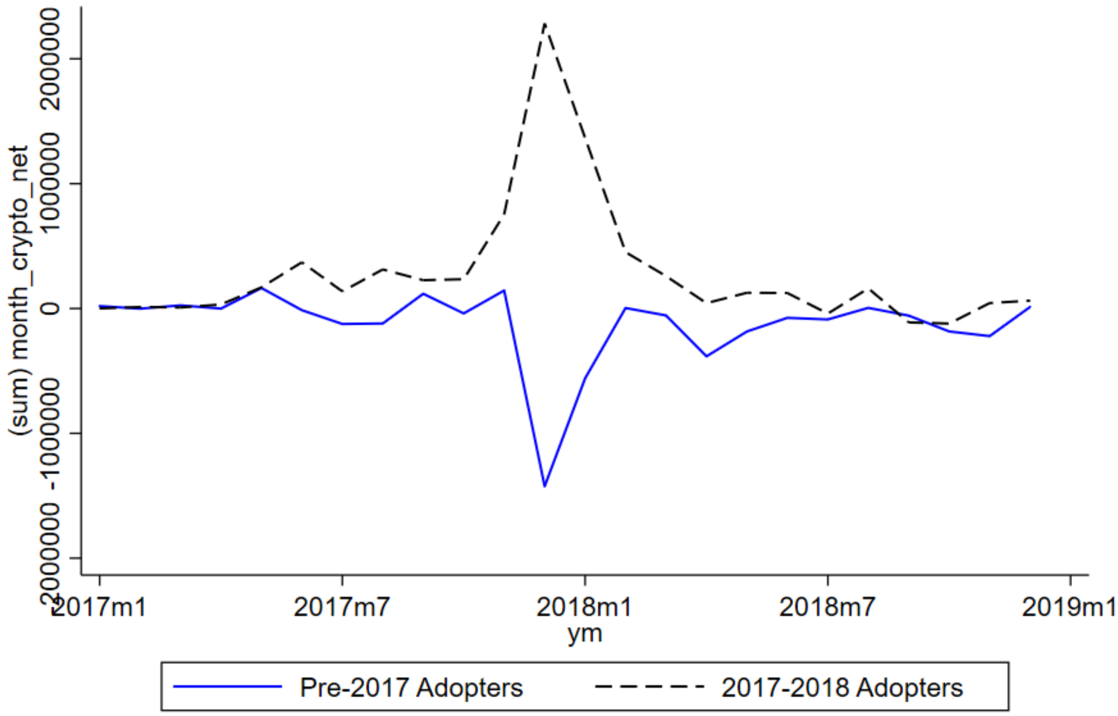


Panel B: Crypto Net Deposits



This figure shows the relation between retail crypto activity and Bitcoin prices. Panel A shows withdrawals or redemption of crypto. Panel B shows the net deposits into crypto which is the total deposits minus withdrawals.

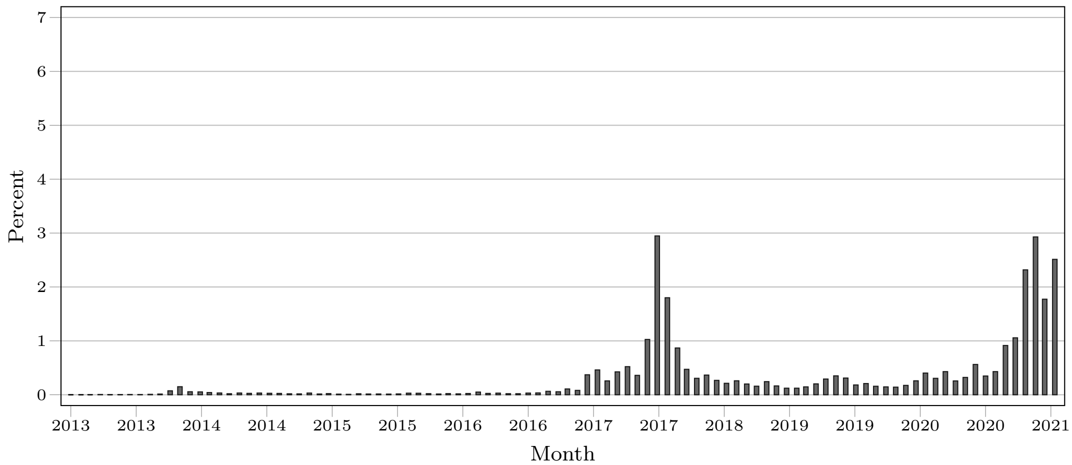
Figure 3. Net Deposits (Withdrawals) by Crypto Adoption Cohort



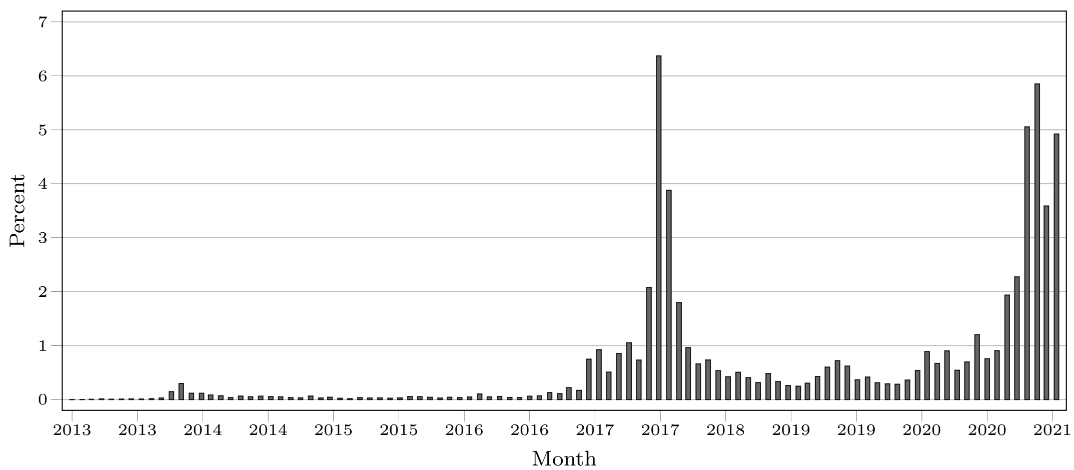
This figure plots net deposits to (and net withdrawals from) cryptocurrency exchanges, splitting the sample into those who first interacted with an exchange prior to or after 2017. We note substantial net withdrawals from exchanges by pre-2017 adopters and substantial net deposits from those adopting in 2017–2018.

Figure 4. Crypto Investment Share

Panel A: Monthly Cryptocurrency Investment as a Percentage of Total Debits

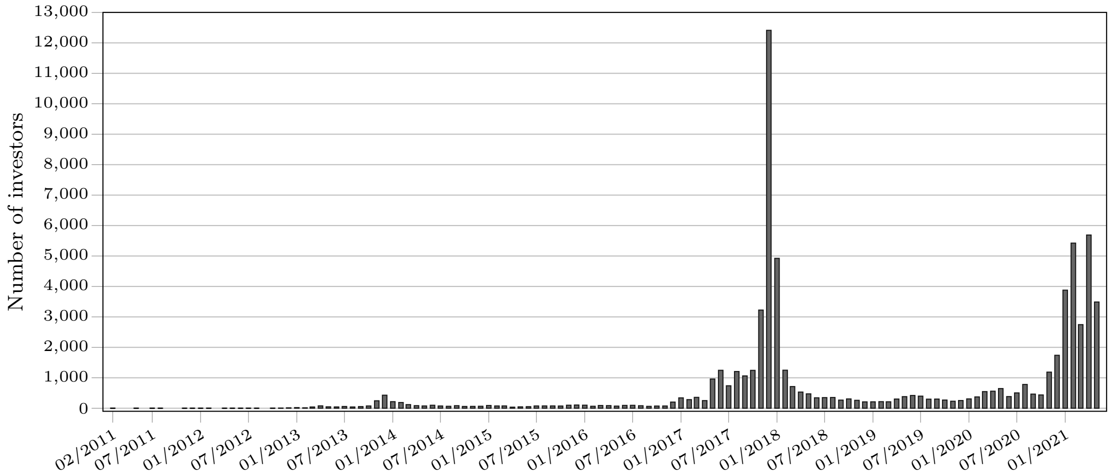


Panel B: Monthly Cryptocurrency Investment as a Percentage of Total Spending



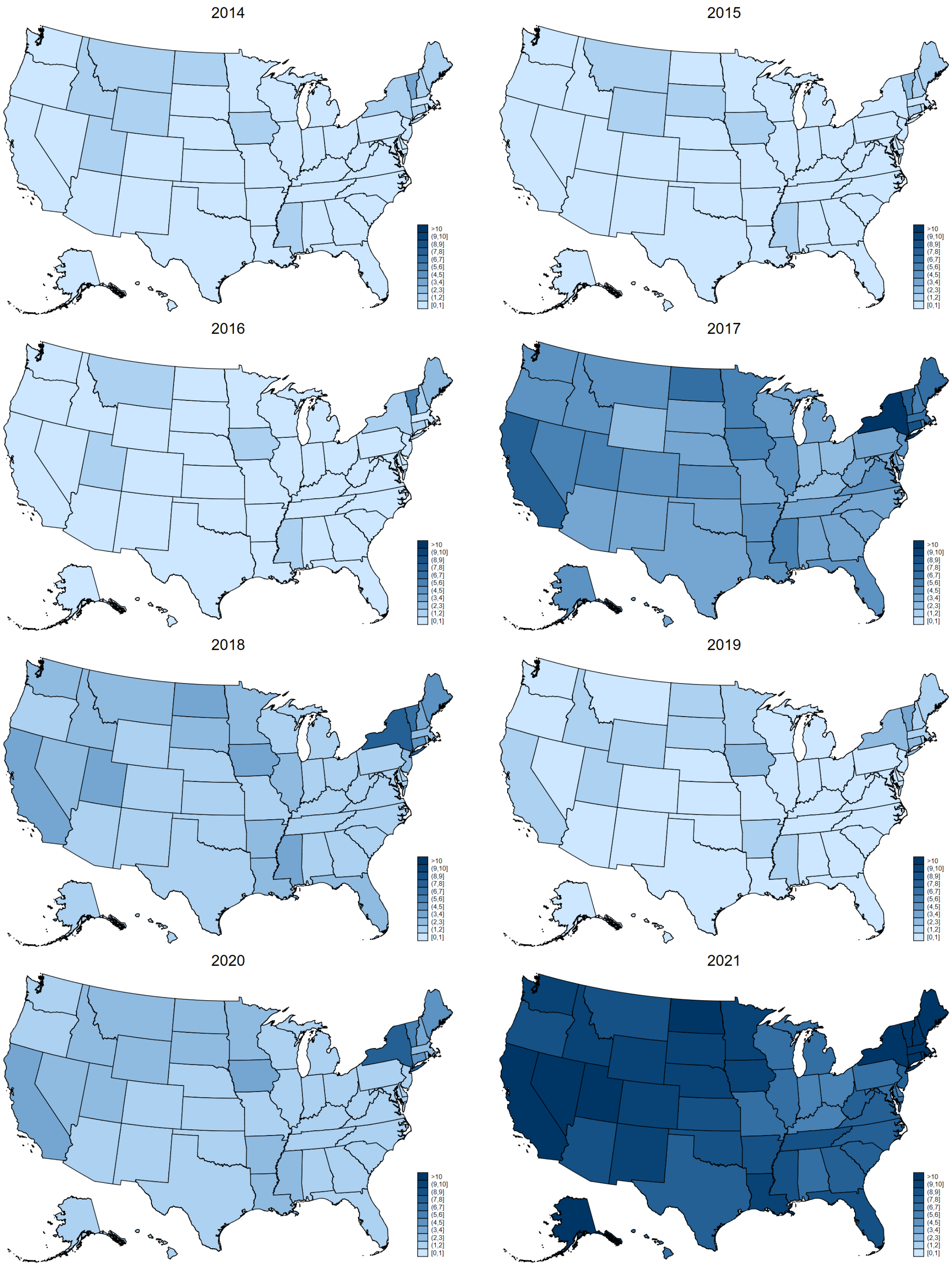
The figure above illustrates the share of cryptocurrency retail investment. Panel A plots monthly dollar cryptocurrency investment amount as a percentage of total debits. Panel B plots monthly dollar cryptocurrency investment amount as a percentage of total spending.

Figure 5. Number of New Cryptocurrency Investors by Year



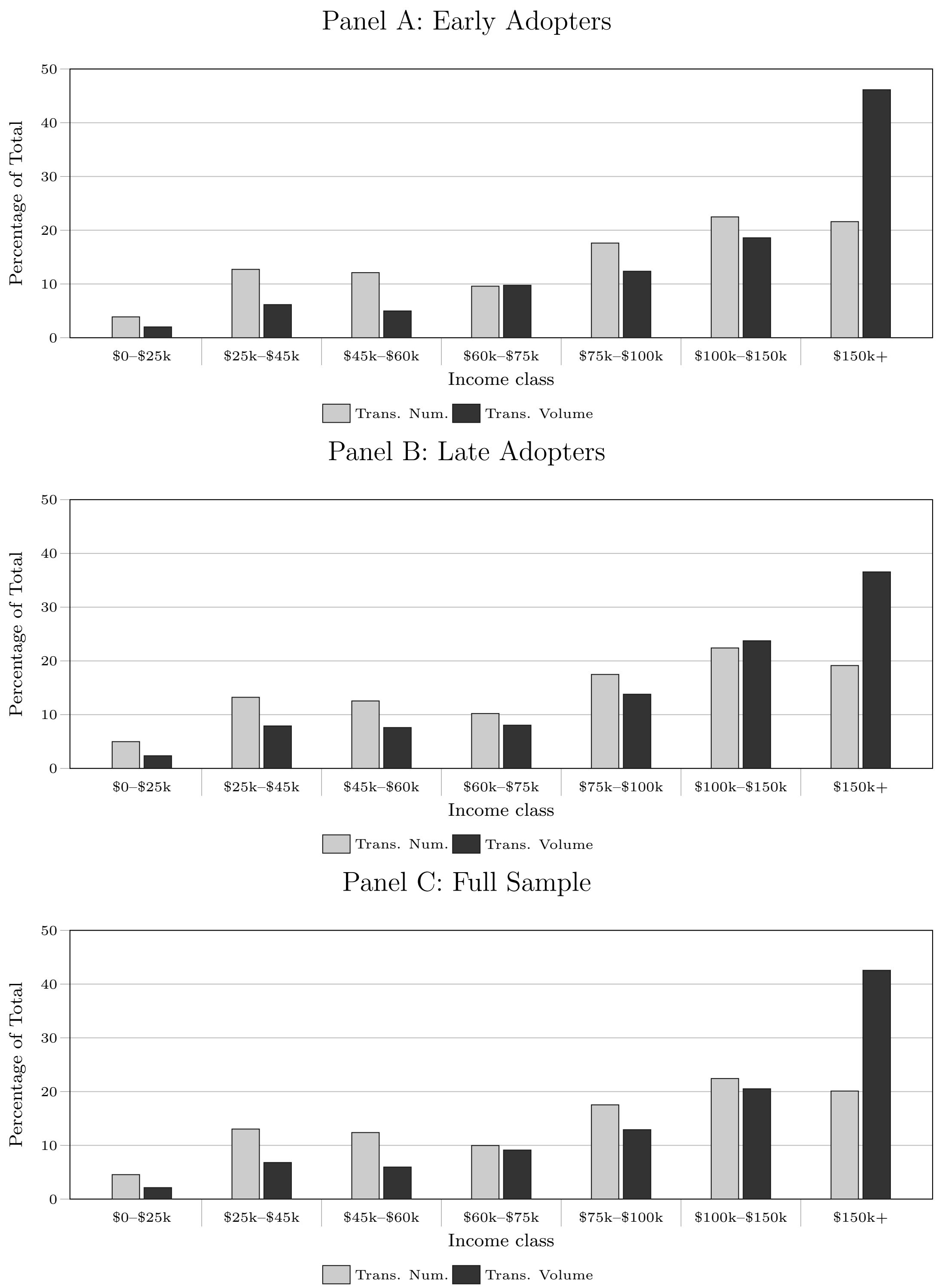
This figure above plots the number of new cryptocurrency investors from the beginning of the year 2011 to the end of the year 2020.

Figure 6. Crypto Investment: New Crypto Users per 1,000 Households



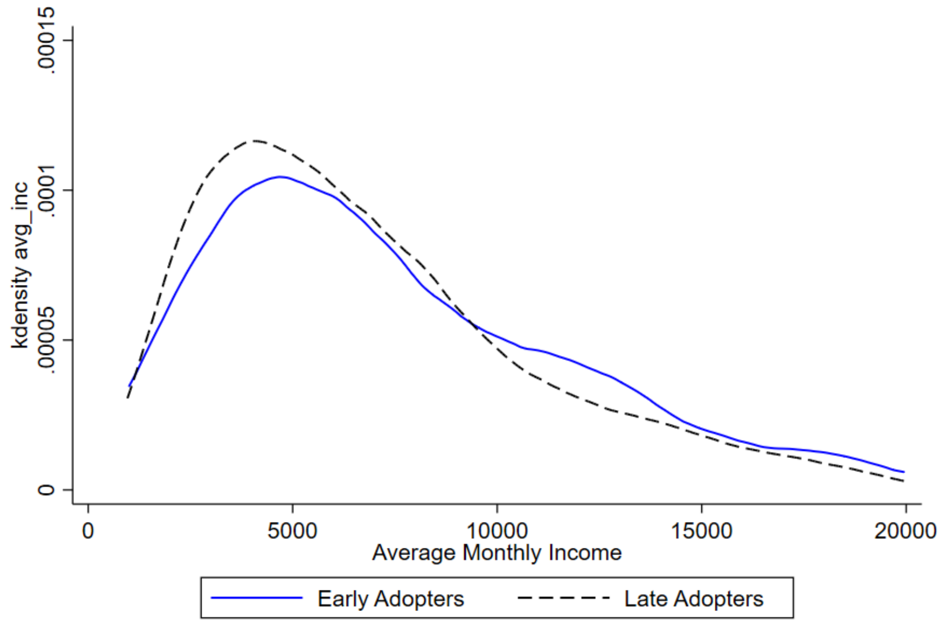
This figure above illustrates the number of new cryptocurrency investors scaled by the number of households (in thousand) for different states in the U.S. from the year 2017 to the year 2020.

Figure 7. Percentage of Investors by Income Class, as of December 2019



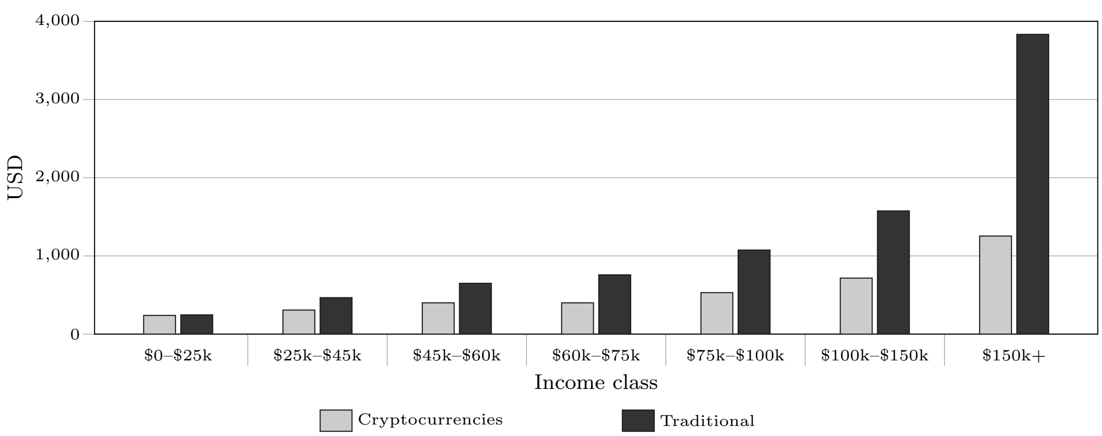
This figure displays the distribution of cryptocurrency investment across income classes by number of transactions and dollar volume. Panel A plots the distribution of cryptocurrency investment by income class for cryptocurrency investors who began investing in crypto prior to the 2017 highs. Panel B plots the distribution of cryptocurrency investment by income class for cryptocurrency investors who began investing in crypto after the 2017 highs. Panel C plots the distribution of cryptocurrency investment by income class for the entire sample of cryptocurrency investors.

Figure 8. Average Income of Crypto Adopters



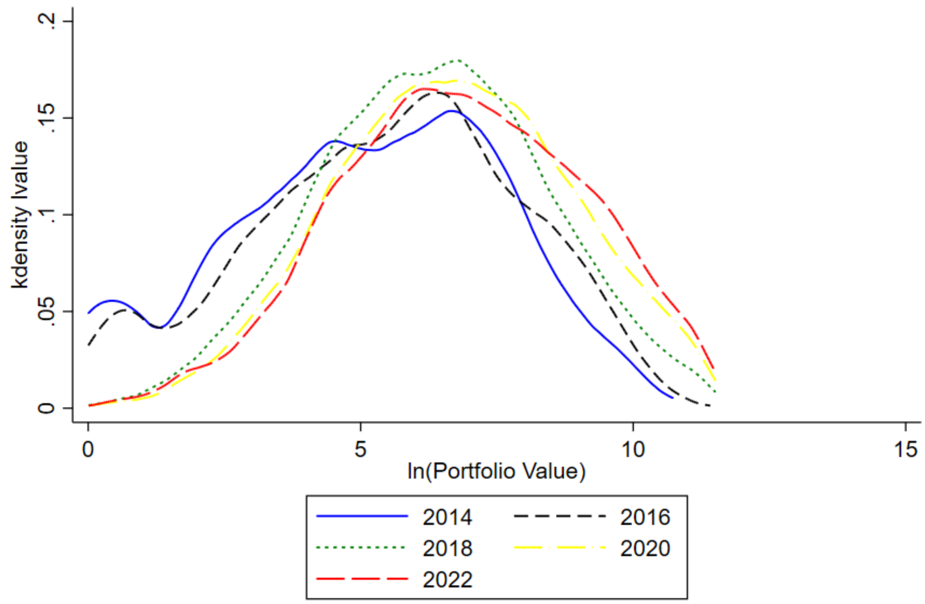
This figure plots kernal density plots of average monthly income by user. Sample is split according to the time that they were first observed to interact with a cryptocurrency exchange. Early adopters are defined as those who first interacted with an exchange prior to 2019 and late adopters are those who first interacted with an exchange in 2019 or afterwards.

Figure 9. Median Annual Investment by Asset and Income Class



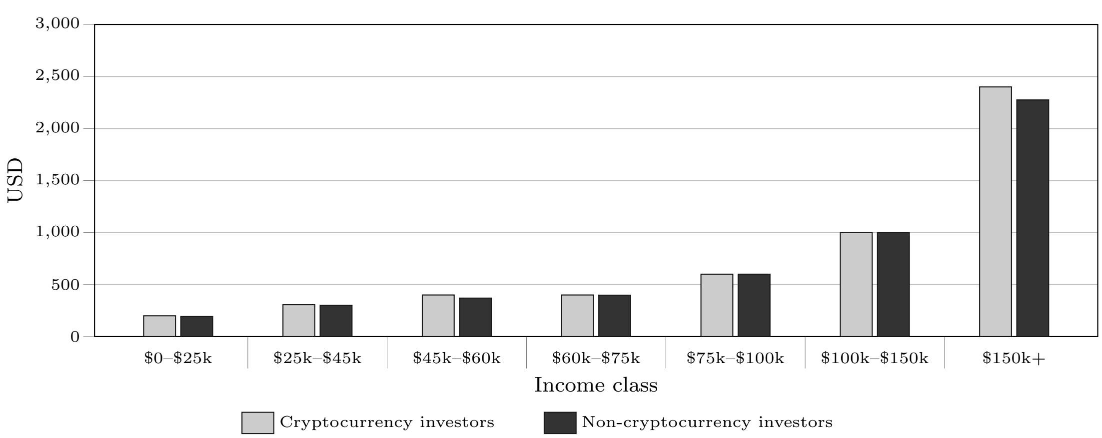
This figure displays the distribution of traditional investment and cryptocurrency investment across asset and income classes by dollar volume.

Figure 10. Crypto Portfolio Distribution Across Individuals, by Year



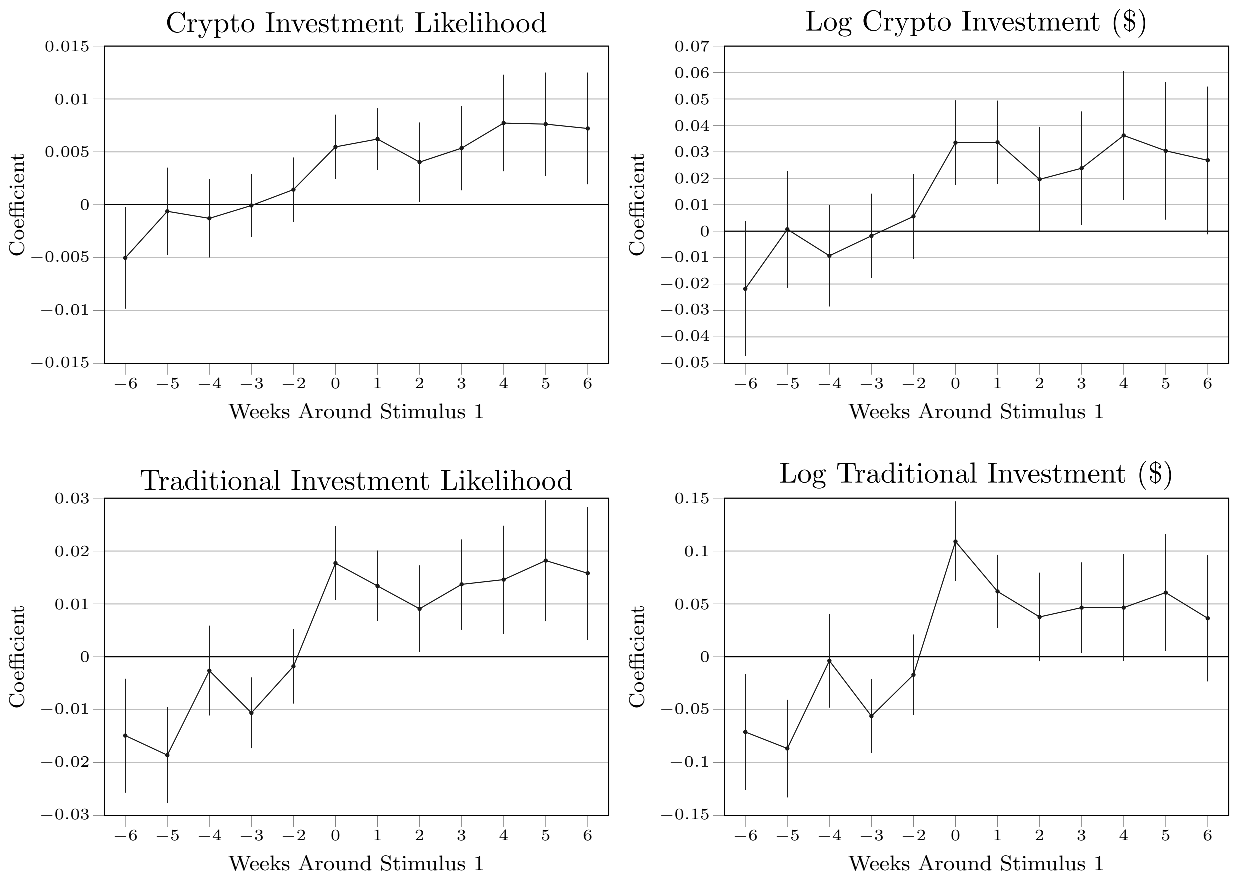
This figure plots kernel density plots of total imputed crypto account balances across users, splitting by year for selected years.

Figure 11. Traditional Investment: Crypto v. Non-Crypto Investors



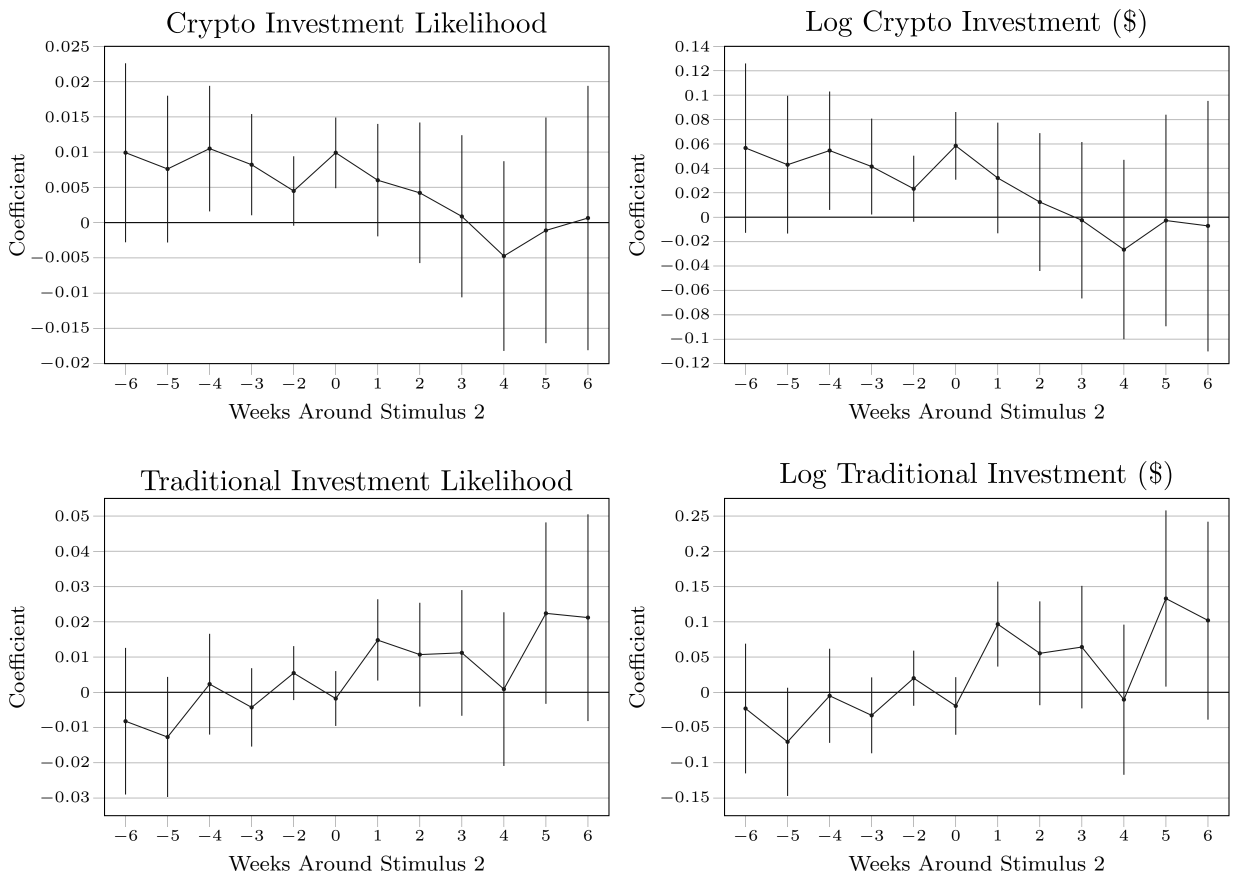
This figure displays the distribution of traditional investment across income classes by dollar volume for cryptocurrency and non-cryptocurrency investors.

Figure 12. Retail Investment Responses After Stimulus I



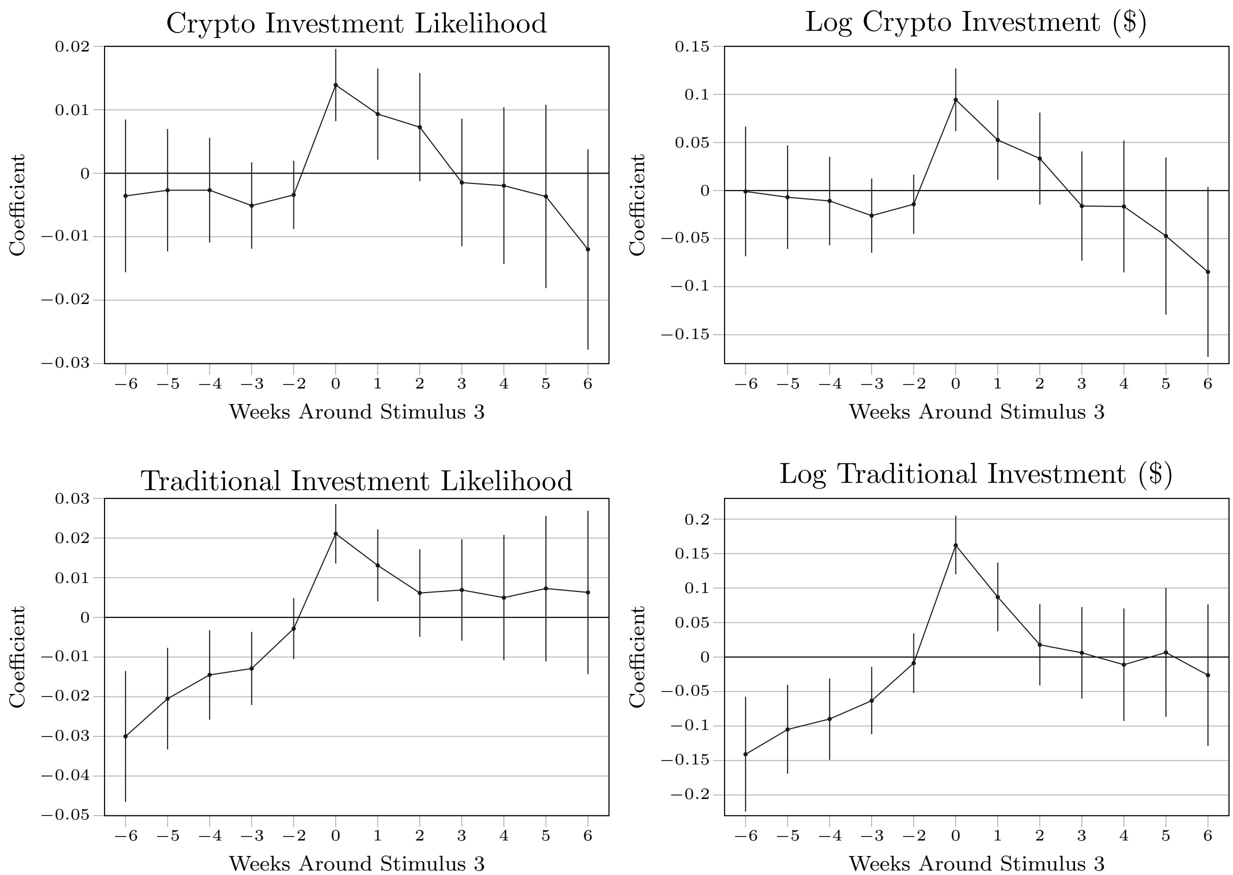
This figure displays the difference in cryptocurrency and traditional investment before v. after receiving the first stimulus check. All figures plot β_k from equation (3) for the likelihood of investing and the log dollar amount invested in either asset class.

Figure 13. Retail Investment Responses After Stimulus II



This figure displays the difference in cryptocurrency and traditional investment before v. after receiving the second stimulus check. All figures plot β_k from equation (3) for the likelihood of investing and the log dollar amount invested in either asset class.

Figure 14. Retail Investment Responses After Stimulus III



This figure displays the difference in cryptocurrency and traditional investment before v. after receiving the third stimulus check. All figures plot β_k from equation (3) for the likelihood of investing and the log dollar amount invested in either asset class.

Table I. Summary Statistics

		Full Sample	Crypto Investors	Crypto Investors & Early Adopters	Crypto Investors & Late Adopters	Crypto Investors & Covid Adopters	Crypto Investors & Stimulus Recipients
Likelihood of Ever Using Overdrafts	(%)	32.78	31.95	34.15	30.41	27.60	30.14
Likelihood of Ever Using a Credit Card	(%)	97.27	99.01	98.98	99.04	99.20	99.31
Likelihood of Ever Gambling	(%)	38.79	52.51	53.47	51.84	51.58	52.92
Likelihood of Ever Being a Homeowner	(%)	61.64	66.01	65.35	66.47	66.17	66.15
Likelihood of Ever Being Unemployed	(%)	14.99	16.65	15.55	17.41	19.00	18.86
Likelihood of Ever Being Hand-to-Mouth	(%)	11.87	8.65	7.10	9.75	10.38	8.88
Nonphysical Transactions	(%)	49.41	52.38	54.79	50.69	48.00	50.01
Salary Income		3,290	3,596	3,603	3,591	3,351	3,403
Total Spending		7,008	7,725	8,356	7,281	5,999	6,559
Spending on Housing		577	651	683	629	531	565
Credit Card Spending		1,829	2,204	2,455	2,028	1,549	1,764
N		812,691	96,071	39,642	56,429	23,612	64,534

This table reports summary statistics for different subsets of the sample. The top panel reports frequencies, while the bottom panel reports means. The first column displays summary statistics for the full sample, which includes both crypto and non-crypto investors. The second column displays summary statistics for crypto investors only. The third column displays summary statistics for crypto investors who began investing in the crypto space prior to the 2017 highs. The fourth column displays summary statistics for crypto investors who began investing in the crypto space after the 2017 highs. The fifth column displays summary statistics for crypto investors who are are also stimulus recipients. The sixth column reports summary statistics for crypto investors who are stimulus recipients and who began investing in the crypto space prior to the 2017 highs. The seventh column reports summary statistics for crypto investors who are stimulus recipients and who began investing in the crypto space after the 2017 highs.

Table II. Zip Demographics

This table shows sample means and standard deviations [in brackets] of zip code-level characteristics based on the imputed home zip code of users. Note that we only identify zip codes for 48% of users. Data is based on a user-level panel of monthly transaction data. Early adopters are defined as first investing in crypto before January 2018, while late adopters first invest in crypto after December 2017. Never adopters do not use crypto during our sample period of 2014–2022.

Panel A: Race and Ethnicity

Variable	Early Adopter	Late Adopter	Never Adopter
% White	69.8	70.1	69.6
	[17.2]	[17.9]	[18.8]
% Black	11.1	12.5	12.1
	[13.2]	[14.2]	[14.5]
% Hispanic	16.9	16.5	17.0
	[15.6]	[16.5]	[17.1]
% Non-Hispanic White	59.7	60.3	59.7
	[20.8]	[22.0]	[22.8]
% U.S. Native	83.9	86.2	85.0
	[11.9]	[11.2]	[12.1]
Panel B: Age and Education			
Median Age	38.1	37.9	38.5
	[5.5]	[5.8]	[5.8]
% Male	49.1	49.2	49.1
	[2.9]	[3.0]	[2.8]
% Military	1.0	1.5	1.1
	[4.6]	[5.7]	[5.0]
% Less than High School	8.3	8.5	8.8
	[6.0]	[5.9]	[6.2]
% High School	20.8	22.7	22.7
	[9.0]	[9.1]	[9.2]
% Some College	26.9	28.8	28.1
	[8.4]	[7.9]	[7.8]
% College	25.6	24.0	24.0
	[9.0]	[8.8]	[8.7]
% Grad School	18.3	16.1	16.4
	[10.6]	[9.7]	[10.0]
Panel C: Zip Code Size			
Population	38,296	36,349	36,505
	[19,630]	[19,332]	[19,025]
Tot. Households	14,550	13,588	13,673
	[7,013]	[6,741]	[6,708]

Panel D: Income

Variable	Early Adopter	Late Adopter	Never Adopter
Median HH Income	84,829	79,215	80,597
	[32,431]	[29,256]	[30,356]
Avg. HH Income	112,038	102,603	104,904
	[45,940]	[39,264]	[41,840]
Avg. HH Earnings	112,312	101,801	104,578
	[46,516]	[39,054]	[41,839]
Avg. HH Soc. Sec.	20,665	20,463	20,584
	[3,093]	[2,933]	[2,970]
Median Family Income	104,387	96,579	98,446
	[41,899]	[35,909]	[37,834]
Avg. Family Income	133,227	120,816	123,817
	[60,575]	[49,946]	[53,972]
% Foodstamps	6.9	7.4	7.5
	[5.6]	[5.7]	[5.8]

Panel E: Occupation

% Managerial/Professional	47.1	44.1	44.3
	[14.1]	[13.1]	[13.3]
% Services	15.7	16.3	16.3
	[5.6]	[5.3]	[5.5]
% Sales/Office	20.9	21.5	21.5
	[3.7]	[3.7]	[3.7]
% Farming	0.3	0.3	0.3
	[0.9]	[1.0]	[0.9]
% Construction	6.3	7.0	6.9
	[3.5]	[3.7]	[3.6]
% Transportation	9.7	10.7	10.7
	[5.5]	[5.5]	[5.5]

Panel F: Industry

Variable	Early Adopter	Late Adopter	Never Adopter
% Agriculture	0.9	1.0	0.9
	[1.8]	[2.1]	[1.8]
% Construction	5.5	5.9	5.9
	[2.7]	[2.7]	[2.8]
% Manufacturing	8.1	8.3	8.3
	[4.7]	[4.9]	[5.0]
% Wholesale Trade	2.5	2.4	2.5
	[1.2]	[1.2]	[1.2]
% Retail Trade	10.4	10.8	10.8
	[3.0]	[2.9]	[3.0]
% Transportation	4.8	5.0	5.1
	[2.4]	[2.4]	[2.5]
% Information	2.6	2.2	2.3
	[2.2]	[1.7]	[1.8]
% Finance	8.1	7.4	7.6
	[4.5]	[3.6]	[3.9]
% Professional	14.7	13.4	13.5
	[6.4]	[5.8]	[5.7]
% Education/Health	23.0	23.2	23.4
	[5.6]	[5.5]	[5.5]
% Recreation	9.6	9.7	9.5
	[3.9]	[3.8]	[3.7]
% Other	4.6	4.7	4.8
	[1.5]	[1.5]	[1.5]
% Public Admin.	5.3	5.8	5.5
	[4.1]	[4.6]	[4.3]

Table III. Cryptocurrency Investment Flows in Response to BTC Prices

	Dependent variable		
	% Chg Debits	% Chg Credits	% Chg Net Flows
	(1)	(2)	(3)
BTC Return (%)	1.115**	0.431	1.075
	(2.112)	(0.997)	(0.694)
Lag(BTC Return (%), 1)	1.097***	1.413***	0.219
	(4.998)	(3.551)	(1.490)
Constant	−0.032	6.948	37.923
	(4.572)	(1.352)	(1.490)
Observations	79	79	79
R^2	0.301	0.248	0.016
Adjusted R^2	0.283	0.228	−0.010
Residual Std. Error (df = 76)	60.645	62.847	209.929
F Statistic (df = 2; 76)	16.356***	12.529***	0.620

This table reports estimates from equation (3). The first column reports OLS estimates of the response of percent changes in cryptocurrency debits to percent changes in Bitcoin prices. The second column reports OLS estimates of the response of percent changes in cryptocurrency credits to percent changes in Bitcoin prices. The third column reports OLS estimates of the response of percent changes in cryptocurrency net flows, computed as the difference between credits and debits, to percent changes in Bitcoin prices. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are clustered at the person level are presented in parentheses.

Table IV. Traditional Investment Flows in Response to S&P 500 Prices

	Dependent variable		
	% Chg Debits	% Chg Credits	% Chg Net Flows
	(1)	(2)	(3)
S&P 500 Return (%)	−1.129	0.331	−1.455
	(−1.099)	(1.150)	(−1.162)
Lag(S&P 500 Return (%), 1)	0.022	0.436	−0.138
	(0.038)	(1.191)	(−0.187)
Constant	3.474	1.865*	4.252
	(1.619)	(1.700)	(1.584)
Observations	98	98	98
R^2	0.061	0.018	0.075
Adjusted R^2	0.042	−0.002	0.055
Residual Std. Error (df = 95)	17.492	14.964	20.071
F Statistic (df = 2; 95)	3.104**	0.880	3.842**

This table reports estimates from equation (3) for traditional investment. The first column reports OLS estimates of the response of percent changes in traditional investment debits to percent changes in S&P 500 prices. The second column reports OLS estimates of the response of percent changes in traditional investment credits to percent changes in S&P 500 prices. The third column reports OLS estimates of the response of percent changes in traditional investment net flows, computed as the difference between credits and debits, to percent changes in S&P 500 prices. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are clustered at the person level are presented in parentheses.

Table V. Stimulus MPI by Investor Characteristics and Timing of Investment

Panel A: Crypto Investment ($)

	Crypto Investment						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total Credit	0.00509***	0.00880***	0.00414***	0.00406***	0.00494***	0.00533***	-0.000888
	(7.44)	(12.07)	(5.31)	(5.34)	(6.81)	(7.41)	(-1.15)
Total Credit x Early Adopter		-0.00949***					
		(-12.98)					
Total Credit x Gambler			0.00179**				
			(2.51)				
Total Credit x Hand-to-Mouth				0.00179**			
				(2.37)			
Total Credit x Overdrafter					0.000676		
					(0.75)		
Total Credit x Unemployed						-0.00127	
						(-1.43)	
Total Credit x Covid Adopter							0.0141***
							(19.16)
N	1,505,855	1,505,855	1,505,794	1,505,794	1,505,794	1,505,794	1,505,855
R-squared	-0.00935	-0.0328	-0.0109	-0.00817	-0.00950	-0.00988	-0.0618
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Income Class x Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Traditional Investment ($)

	Traditional Investment						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total Credit	0.00823***	0.00974***	0.00576***	0.00999***	0.00769***	0.00811***	0.00371*
	(4.73)	(5.32)	(2.93)	(4.96)	(4.20)	(4.45)	(1.89)
Total Credit x Early Adopter		-0.00385**					
		(-2.00)					
Total Credit x Gambler			0.00458**				
			(2.49)				
Total Credit x Hand-to-Mouth				-0.00311			
				(-1.57)			
Total Credit x Overdrafter					0.00219		
					(0.95)		
Total Credit x Unemployed						0.000497	
						(0.23)	
Total Credit x Covid Adopter							0.0107***
							(5.90)
N	1,505,855	1,505,855	1,505,794	1,505,794	1,505,794	1,505,794	1,505,855
R-squared	0.00768	0.00721	0.00689	0.00667	0.00757	0.00769	0.00393
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Income Class x Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports estimates from IV regression (4b). This specification includes person and state x income class x week fixed effects. The first column reports IV estimates for the baseline model. The second column reports IV estimates for the interaction of total credit with a dummy that flags investors who began investing in the crypto space prior to the 2017 highs. The third column reports IV estimates for the interaction of total credit with a dummy that flags investors who gambled at least once over the sample period. The fourth column reports IV estimates for the interaction of total credit with a dummy that flags investors who tend to consume most of their income. The fifth column reports IV estimates for the interaction of total credit with a dummy that flags investors who incurred in overdraft fees at least once over the sample period. The sixth column reports IV estimates for the interaction of total credit with a dummy that flags investors who have been unemployed at least once over the sample period. The seventh column reports IV estimates for the interaction of total credit with a dummy that flags investors who began investing in the crypto space after the onset of Covid-19. Standard errors are clustered at the person level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *t*-statistics are presented in parentheses.

Table VI. Investment Response to Realized, Expected, and Investor-Level Inflation

Panel A: Crypto Investment

	Crypto Investment Likelihood (1/0)			Crypto Investment ($)		
	(1)	(2)	(3)	(4)	(5)	(6)
CPI-U Inflation	0.0254***			10.80***		
	(217.17)			(166.51)		
12-Month E[π]		0.0263***			10.96***	
		(82.84)			(65.87)	
Investor eCPI (Consumption)			0.00803***			2.389***
			(12.52)			(6.92)
N	10,078,700	10,078,700	7,744,321	10,078,700	10,078,700	7,744,321
R-squared	0.0968	0.0861	0.1896	0.0822	0.0756	0.1593
Person FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Income Class FEs	Yes	Yes	No	Yes	Yes	No
State × Income Class × Month FEs	No	No	Yes	No	No	Yes

Panel B: Traditional Investment

	Traditional Investment Likelihood (1/0)			Traditional Investment ($)		
	(1)	(2)	(3)	(4)	(5)	(6)
CPI-U Inflation	0.0199***			9.451***		
	(77.53)			(27.46)		
12-Month E[π]		-0.0419***			-34.88***	
		(-51.87)			(-33.45)	
Investor eCPI (Consumption)			0.0150***			-1.389
			(13.69)			(-0.72)
N	10,078,700	10,078,700	7,744,321	10,078,700	10,078,700	7,744,321
R-squared	0.3426	0.3421	0.421	0.2317	0.2319	0.2968
Person FE	Yes	Yes	Yes	Yes	Yes	Yes
State × Income Class FEs	Yes	Yes	No	Yes	Yes	No
State × Income Class × Month FEs	No	No	Yes	No	No	Yes

This table reports estimates of the response of the dollar amount of crypto investment (Panel A) and traditional investment (Panel B) to realized, expected, and investor-level inflation. Column 1 reports the estimate of the response of crypto investment to aggregate realized inflation as measured by Consumer Price Index for Urban Consumers (*CPI-U Inflation*). Column 2 reports the estimates of the response of crypto investment to 12-month aggregate inflation expectations based on the University of Michigan survey (*12-Month E[pi]*). Column 3 reports the estimate of the response of log crypto investment to investor-level inflation exposure based on consumption categories (*Investor eCPI (Consumption)*). Standard errors are clustered at the person level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *t*-statistics are presented in parentheses.

Table VII. Heterogeneity in Investment Response to Inflation – Risk Attitude & Experience

Panel A: Crypto Investment

	Crypto Investment ($)			
	(1)	(2)	(3)	(4)
Investor eCPI (Consumption)	1.931***	1.657***	7.842***	-0.594
	(5.54)	(4.26)	(21.24)	(-1.64)
Investor eCPI (Consumption) × Sophisticated (1/0)	4.681***			
	(7.49)			
Investor eCPI (Consumption) × Gambler (1/0)		1.355***		
		(3.9)		
Investor eCPI (Consumption) × Early Adopter (1/0)			-13.09***	
			(-37.35)	
Investor eCPI (Consumption) × Covid Adopter (1/0)				12.11***
				(32.24)
N	7,744,321	7,744,321	7,744,321	7,744,321
R-squared	0.1593	0.1593	0.1596	0.1595
Person FE	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

Panel B: Traditional Investment

	Traditional Investment ($)			
	(1)	(2)	(3)	(4)
Investor eCPI (Consumption)	-8.459***	-4.072*	1.275	-3.766*
	(-4.39)	(-1.92)	(0.63)	(-1.87)
Investor eCPI (Consumption) × Sophisticated (1/0)	72.33***			
	(16.94)			
Investor eCPI (Consumption) × Gambler (1/0)		4.965***		
		(2.74)		
Investor eCPI (Consumption) × Early Adopter (1/0)			-6.394***	
			(-3.48)	
Investor eCPI (Consumption) × Covid Adopter (1/0)				9.650***
				(5.12)
N	7,744,321	7,744,321	7,744,321	7,744,321
R-squared	0.2969	0.2968	0.2968	0.2968
Person FE	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

This table reports estimates of the heterogeneous response of the dollar amount of crypto investment (Panel A) and traditional investment (Panel B) to investor-level inflation exposure based on investors' attitudes toward hedging and risk. Column 1 reports the estimates for heterogeneity based on a measure of investors' financial sophistication (*Sophisticated*). Column 2 reports the estimates for heterogeneity based on a measure of investors' propensity to gamble (*Gambler*). Column 3 reports the estimates for heterogeneity based on whether an investor adopted crypto before January 2018 (*Early Adopter*). Column 4 reports the estimates for heterogeneity based on whether an investor adopted crypto during the Covid-19 period after January 2020 (*Covid Adopter*). Standard errors are clustered at the person level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

Table VIII. Heterogeneity in Investment Response to Inflation – Budget Constraints

Panel A: Crypto Investment

	Crypto Investment ($)				
	(1)	(2)	(3)	(4)	(5)
Investor eCPI (Consumption)	0.999**	1.125**	0.423	2.131***	2.599***
	(2.30)	(2.35)	(0.92)	(5.79)	(7.36)
Investor eCPI (Consumption) × Below-Median Income (1/0)	2.207***				
	(5.62)				
Investor eCPI (Consumption) × Salary Volatility		2.878***			
		(5.00)			
Salary Volatility		0.956***			
		(3.67)			
Investor eCPI (Consumption) × Hand-to-Mouth (1/0)			2.827***		
			(6.91)		
Investor eCPI (Consumption) × Overdrafter (1/0)				0.762**	
				(2.04)	
Investor eCPI (Consumption) × Unemployed (1/0)					-1.257***
					(-2.66)
N	7,744,321	6,188,336	7,744,321	7,744,321	7,744,321
R-squared	0.1593	0.1711	0.1593	0.1593	0.1593
Person FE	Yes	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes	Yes

Panel B: Traditional Investment

	Traditional Investment ($)				
	(1)	(2)	(3)	(4)	(5)
Investor eCPI (Consumption)	-3.854	-8.325***	-4.468*	1.989	0.748
	(-1.54)	(-3.08)	(-1.69)	(0.97)	(0.38)
Investor eCPI (Consumption) × Below-Median Income (1/0)	3.913*				
	(1.88)				
Investor eCPI (Consumption) × Salary Volatility		12.23***			
		(3.99)			
Salary Volatility		11.06***			
		(6.71)			
Investor eCPI (Consumption) × Hand-to-Mouth (1/0)			4.430**		
			(2.00)		
Investor eCPI (Consumption) × Overdrafter (1/0)				-9.987***	
				(-5.16)	
Investor eCPI (Consumption) × Unemployed (1/0)					-12.75***
					(-5.52)
N	7,744,321	6,188,336	7,744,321	7,744,321	7,744,321
R-squared	0.2968	0.3115	0.2968	0.2968	0.2968
Person FE	Yes	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes	Yes

This table reports estimates of the heterogeneous response of the dollar amount of crypto investment (Panel A) and traditional investment (Panel B) to investor-level inflation exposure based on investors' budget constraints. Column 1 reports the estimates for heterogeneity based on a dummy for below-median income (*Below-Median Income*). Column 2 reports the estimates for heterogeneity based on investors' 12-month normalized salary volatility (*Salary Volatility*). Column 3 reports the estimates for heterogeneity based on a dummy for hand-to-mount investor (*Hand-to-Mouth*). Column 4 reports the estimates for heterogeneity based on a dummy for consumer ever incurring an overdraft (*Overdrafter*). Column 5 reports the estimates for heterogeneity based on a dummy for consumer ever receiving unemployment benefits (*Unemployed*). Standard errors are clustered at the person level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

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Internet Appendix to "Cryptocurrency Investing: Stimulus Checks and Inflation Expectations"

FOR ONLINE PUBLICATION

Table IA.I. Stimulus I Crypto MPI

	Crypto Investment						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total Credit	0.000227***	0.000193***	0.0000667	0.000427***	0.00141***	-0.000541***	-0.000243***
	(3.90)	(2.76)	(0.75)	(4.65)	(16.69)	(-6.55)	(-2.58)
Total Credit x Overdrafter		0.000120					
		(0.79)					
Total Credit x Gambler			0.000305**				
			(2.46)				
Total Credit x Hand-to-Mouth				-0.000355***			
				(-2.77)			
Total Credit x Pre-Stimulus Crypto Investor					-0.00195***		
					(-16.75)		
Total Credit x Post-Stimulus Crypto Investor						0.00195***	
						(16.75)	
Total Credit x Post-Stimulus Crypto Investor Within Six Weeks							0.0304***
							(8.54)
N	641,211	641,185	641,185	641,185	641,211	641,211	641,211
R-squared	-0.00295	-0.00322	-0.00627	-0.00869	-0.119	-0.119	-1.821
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Income Class x Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports MPI estimates from IV regression (4b). This specification includes person and state x income class x week fixed effects. The coefficient is estimated using the entire sample of cryptocurrency investors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the person level are reported in parentheses.

Table IA.II. Stimulus I Traditional MPI

	Traditional Investment			
	(1)	(2)	(3)	(4)
Total Credit	0.00705***	0.00451***	0.00530***	0.0100***
	(8.12)	(4.38)	(4.15)	(7.24)
Total Credit x Overdrafter		0.00894***		
		(4.19)		
Total Credit x Gambler			0.00328*	
			(1.84)	
Total Credit x Hand-to-Mouth				-0.00531***
				(-2.78)
N	641,211	641,185	641,185	641,185
R-squared	-0.00402	-0.0111	-0.00542	-0.0102
Person FE	Yes	Yes	Yes	Yes
State x Income Class x Week FEs	Yes	Yes	Yes	Yes

This table reports MPI estimates from IV regression (4b).This specification includes person and state x income class x week fixed effects. The coefficient is estimated using the entire sample of cryptocurrency investors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the person level are reported in parentheses.

Table IA.III. Stimulus II Crypto MPI

	Crypto Investment						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total Credit	0.00144***	0.00162***	0.000687	0.000877	0.0112***	-0.00449***	-0.00656***
	(3.75)	(4.03)	(1.31)	(1.55)	(19.09)	(-8.57)	(-10.64)
Total Credit x Overdrafter		-0.00149					
		(-1.59)					
Total Credit x Gambler			0.00139**				
			(2.03)				
Total Credit x Hand-to-Mouth				0.000968			
				(1.34)			
Total Credit x Pre-Stimulus Crypto Investor					-0.0157***		
					(-22.03)		
Total Credit x Post-Stimulus Crypto Investor						0.0157***	
						(22.03)	
Total Credit x Post-Stimulus Crypto Investor Within Six Weeks							0.0573***
							(29.53)
N	525,490	525,451	525,451	525,451	525,490	525,490	525,490
R-squared	0.00256	0.00141	0.000777	0.00282	-0.187	-0.187	-1.106
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Income Class x Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports MPI estimates from IV regression (4b). This specification includes person and state x income class x week fixed effects. The coefficient is estimated using the entire sample of cryptocurrency investors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the person level are reported in parentheses.

Table IA.IV. Stimulus II Traditional MPI

	Traditional Investment			
	(1)	(2)	(3)	(4)
Total Credit	0.000221	0.00158	-0.00433**	-0.00311
	(0.15)	(1.03)	(-2.15)	(-1.43)
Total Credit x Overdrafter		-0.0114***		
		(-3.44)		
Total Credit x Gambler			0.00837***	
			(3.35)	
Total Credit x Hand-to-Mouth				0.00569**
				(2.15)
N	525,490	525,451	525,451	525,451
R-squared	0.000484	-0.00724	-0.00247	-0.00160
Person FE	Yes	Yes	Yes	Yes
State x Income Class x Week FEs	Yes	Yes	Yes	Yes

This table reports MPI estimates from IV regression (4b). This specification includes person and state x income class x week fixed effects. The coefficient is estimated using the entire sample of cryptocurrency investors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the person level are reported in parentheses.

Table IA.V. Stimulus III Crypto MPI

	Crypto Investment						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total Credit	0.00611***	0.00550***	0.00571***	0.00522***	0.0789***	-0.0100***	-0.00813***
	(7.17)	(5.54)	(4.74)	(4.31)	(24.99)	(-7.55)	(-5.55)
Total Credit x Overdrafter		0.00236					
		(1.12)					
Total Credit x Gambler			0.000784				
			(0.45)				
Total Credit x Hand-to-Mouth				0.00162			
				(0.88)			
Total Credit x Pre-Stimulus Crypto Investor					-0.0889***		
					(-25.88)		
Total Credit x Post-Stimulus Crypto Investor						0.0889***	
						(25.88)	
Total Credit x Post-Stimulus Crypto Investor Within Six Weeks							0.117***
							(22.79)
N	600,122	600,070	600,070	600,070	600,122	600122	600,122
R-squared	-0.0063	-0.00678	-0.00673	-0.00561	-1.066	-1.066	-1.405
Person FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Income Class x Week FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports MPI estimates from IV regression (4b). This specification includes person and state x income class x week fixed effects. The coefficient is estimated using the entire sample of cryptocurrency investors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the person level are reported in parentheses.

Table IA.VI. Stimulus III Traditional MPI

	Traditional Investment			
	(1)	(2)	(3)	(4)
Total Credit	0.0150***	0.0140***	0.0159***	0.0196***
	(9.29)	(7.51)	(7.17)	(8.72)
Total Credit x Overdrafter		0.00412		
		(1.08)		
Total Credit x Gambler			-0.00161	
			(-0.52)	
Total Credit x Hand-to-Mouth				-0.00829**
				(-2.48)
N	600,122	600,070	600,070	600,070
R-squared	-0.0132	-0.0132	-0.0130	-0.0205
Person FE	Yes	Yes	Yes	Yes
State x Income Class x Week FEs	Yes	Yes	Yes	Yes

This table reports MPI estimates from IV regression (4b). This specification includes person and state x income class x week fixed effects. The coefficient is estimated using the entire sample of cryptocurrency investors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors clustered at the person level are reported in parentheses.

Table IA.VII. Definitions of Variables

Variable	Definition
Investments and Consumption	
Crypto Investment ($)	Sum of all debits where merchant name or transaction description contains the name of a crypto trading venue (e.g., crypto exchange) in a given period (month or week, as appropriate)
Crypto Investment Likelihood (1/0)	Dummy for making a crypto deposit in a given period (month or week, as appropriate)
Traditional Investment ($)	Sum of all debits where the transaction category is "Securities trades" in a given period (month or week, as appropriate)
Traditional Investment Likelihood (1/0)	Dummy for making a deposit to traditional or FinTech brokerage from bank account or via credit card in a given period (month or week, as appropriate)
% Chg Debits (%)	Percent change in the sum of all debits (i.e., deposits) for crypto or traditional investments in a given period (month or week, as appropriate)
% Chg Credits (%)	Percent change in the sum of all credits (i.e., withdrawals) for crypto or traditional investments in a given period (month or week, as appropriate)
% Chg Net Flows (%)	Percent change in the sum of all credits (i.e., deposits) minus the sum of all credits (i.e., withdrawals) for crypto or traditional investments in a given period (month or week, as appropriate)
BTC Return (%)	Bitcoin return, represented by the percent change of Bitcoin price from the previous year to this year.
BTC Price ($)	Bitcoin price in U.S. dollars
BTC Volume (#)	Bitcoin trading volume
S&P 500 Return (%)	Return on S&P 500 Index
Total Debits ($)	Sum of all debits (i.e., spending) in a given period (month or week, as appropriate)
Total Credits ($)	Sum of all credits (i.e., income) in a given period (month or week, as appropriate)
Salary Income ($)	Salary income in a given month
Salary Volatility ($)	Standard deviation of salary income over the past 12 months divided by total salary income over the past 12 months
Spending on Housing ($)	Sum of all house spending transactions in a given month
Credit Card Spending ($)	Sum of all credit card transactions in a given month
Investor Characteristics	
Sophisticated (1/0)	Dummy for investor ever worked for the top 200 finance firms (defined in order of the number of debit transactions labeled "Securities Trades" per primary merchant)
Gambler (1/0)	Dummy for investor ever transacting at casinos, lottery kiosks, play centers, or betting websites (as inferred from transaction descriptions and primary merchant names)
Early Adopter (1/0)	Dummy that equals to 1 for consumers who invested in crypto for the first time prior to January 2018 and 0 otherwise
Late Adopter (1/0)	Dummy that equals to 1 for consumers who invested in crypto for the first time after January 2018
Covid Adopter (1/0)	Dummy that equals to 1 for consumers who invested in crypto for the first time in January 2020 or thereafter and 0 otherwise
Below-Median Income (1/0)	Dummy for investors' income being below the sample median income

Hand-to-Mouth (1/0)	Dummy for difference between total credits and total debits over the past 2 months being less than $400 more than 50% of time for a consumer in the data set
Overdrafter (1/0)	Dummy that equals 1 if an investor has ever incurred in overdraft fee and 0 otherwise
Unemployed (1/0)	Dummy that equals 1 if an investor has ever received unemployment benefits
Stimulus Payments	
Stimulus I, II, III	Stimulus check payments by round
Realized, Expected, and Investor-Level Inflation	
CPI-U Inflation	Consumer price index for all urban consumers from the Bureau of Labor Statistics (BLS), which measures aggregate realized inflation based on a market basket of consumer goods and services on a monthly basis
12-Month E[π]	University of Michigan survey-based measure of inflation expectations, which measures the median expected price change over the following 12 months across all surveyed consumers on a monthly basis
Investor eCPI (Consumption)	Measure of inflation exposure at the consumer-month level constructed based on monthly changes in the CPI across regions (e.g., Northeast, Midwest, West, and South) and categories of expenditures (e.g., fuel, groceries) from the Bureau of Labor Statistics (BLS), weighted using the weights of these categories in each individual's consumption basket over the preceeding 12 months