Who Invests in Crypto? Wealth, Financial Constraints, and Risk Attitudes*

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ABSTRACT

We provide a first look into who invests in cryptocurrencies and the drivers of retail cryptocurrency investing. We use consumer transaction data to examine how household characteristics, liquidity shocks, risk attitudes, and hedging motives shape the crypto investment decisions of millions of U.S. households. We find that, with the exception of high-income very early adopters, crypto investors closely resemble the general population. Similar to traditional equity investments, while crypto investors exist across the income spectrum, most retail crypto dollars come from high-income individuals. We demonstrate that households increase their investments in crypto following income shocks that relax their budget constraints. Households with higher inflation expectations also increase crypto investing, consistent with hedging motives. Our results suggest that, for most U.S. households, cryptocurrencies are treated much like traditional assets.

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

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

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Cryptocurrency adoption and investment has experienced significant growth in recent years, with an estimated 20% of U.S. households holding some crypto as a part of their portfolios. This growth has attracted the attention of policymakers throughout the world.[1] One of the key concerns of this growth is that it represents an increase in exposure to risks most households may not fully understand. Due to the anonymous nature of public blockchains, it has only been possible to speculate about what has been driving 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 a "fear of missing out."[2] Another popular theory suggests that the fixed supply of cryptocurrency makes it a good inflation hedge.[3]

In this paper, we use unique transaction-level data covering a representative sample of millions of individuals in the U.S. over multiple years to characterize the meaningful drivers of cryptocurrency investment.[4] In contrast to equity investments, crypto investments are highly sensitive to market returns, but the households that participate in crypto are largely similar in terms of characteristics to everyone else. Households respond to unexpected income shocks by investing in both cryptocurrency and traditional assets. In our sample, only 5% of crypto investors lack traditional after-tax investment activity, and of all users without traditional investments only 3% hold crypto. Households invest more in crypto when their inflation expectations are high, consistent with hedging motives. Overall, the households that invest in crypto are similar to those that don't, and the drivers of their behavior are similar to the drivers of investment in traditional asset classes.

We identify individual cryptocurrency purchases and sales by observing transactions directly between user bank accounts or credit cards and the largest US cryptocurrency trading platforms and exchanges like Coinbase.[5] Although the cryptocurrency transactions themselves are recorded on publicly available blockchains, our consumer financial transaction data has several advantages. First, while blockchain data provides detailed information about crypto transactions, it cannot provide any insight into who is behind an anonymous

[1] 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`.

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

[3] 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.

[4] For a detailed look at how the vast increase in cryptocurrency wealth has filtered through to the general economy, tracing its impact on consumers and overall economic activity, see Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter (2023).

[5] Survey evidence shows that Coinbase alone routed more than 62% of the crypto transaction volume in the U.S. as of February 2023. See "Cryptocurrency exchanges used by consumers in the United States from 2021 to 2023," *Measure Protocol*, May 2, 2023.

wallet address nor into consumers who have never invested in cryptocurrencies. As described in detail below, we identify cryptocurrency investing via deposits to and withdrawals from major cryptocurrency trading venues, which we obtain through transaction descriptions in bank and credit card accounts. Second, the data gives us a more comprehensive view of investors' finances: income, spending, and other types of investments beyond cryptocurrency. Since we observe all of the transactions in user bank and credit card accounts, we can also identify numerous other key transactions, including whether the investors received stimulus payments. Finally, the data are provided directly by major U.S. banks that have disclosed these transactions to a data aggregator, ensuring that the data are not subject to selection concerns related to whether the consumers have opted to join a specific financial planning platform that observes their information. Overall, our data provide the first granular view of the finances of retail cryptocurrency investors, allowing us to address gaps in existing literature and policy discourse.

We begin our analysis by documenting several key facts about retail cryptocurrency investing. We test whether the performance of a major cryptocurrency, Bitcoin, contributed to the subsequent entry of new investors in the asset class. We observe a tight correlation between crypto investments and returns of Bitcoin on both the extensive and intensive margins. 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. However, investors who adopted crypto before the boom in crypto prices behave differently than those who adopted it during the run-up. In both time periods, early adopters withdraw crypto during the boom while newer adopters pile in. In contrast to the strong relation between crypto returns and investments, we find no correlation between investments in traditional brokerage accounts and the performance of equity markets. Cryptocurrency transaction volume is concentrated in the most populous states, such as California and New York, but investment growth has been widespread across the United States.

Next, by connecting investors' actual transaction data with zip-level characteristics, we provide detailed insights into the characteristics of cryptocurrency investors across two dimensions. First, we seek to understand how the financial characteristics of new crypto investors have evolved over time. Specifically, we compare investors that entered the market early (which we define as first investing prior to the 2017 Bitcoin price run up), with those that entered at the market's peak, along measures of income, financial constraints, and indicators for attitudes towards risk. We find that these early adopters have relatively higher income and spending and are more likely to be financially sophisticated. Additionally, they are more likely to live in wealthier, more educated zip codes with a higher concentration of professional industries and managerial occupations. Second, we find that—relative to households that do not invest in crypto—crypto investors have higher income and spending, are half as likely to be hand-to-mouth and are 1.5 times as likely to have ever gambled. Crypto investors are somewhat more likely to actively invest in traditional asset classes than non-crypto investors are (80% vs. 60%), but invest similar amounts whey they do. Overall, these results suggest that, in general, crypto investors exhibit higher incomes and financial stability—an effect even more pronounced for those who adopted crypto earlier rather than later.

Having explored crypto investors' characteristics and the relation between returns and investment, we next test whether increases in liquidity affect households' propensity to invest in risky asset classes like crypto. 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—consistent with the spirit of expansionary policies. On the other hand, it is also plausible that more fragile investors take advantage of this liquidity by improving their financial health. To explore these questions, we examine the response of retail crypto investing to (endogenous) positive income shocks in an event study framework. Crypto investment jumps up in the first two weeks after these shocks. The effect is almost three times larger for temporary shocks, but decreases rapidly in the following four weeks while the effect of permanent shocks lasts. We find similar patterns of traditional investment response to these income shocks, with larger sensitivity to the shocks but similar magnitudes once we account for traditional investments being generally larger than crypto investments.

We also examine the response of crypto (and traditional) investment withdrawals to negative income shocks. We find strong effects of temporary negative shocks, which last for about two weeks and disappear in the following weeks, but no effect of permanent negative shocks. However, the propensity to withdraw crypto and traditional investments is essentially the same after temporary negative shocks, suggesting some rebalancing of crypto investors' portfolios toward riskier investments after they take out cash in response to liquidity needs. Non-crypto investors adjust their traditional investments to income shocks in similar manner as crypto investors.

We then exploit the fiscal measures enacted during the Covid-19 pandemic as a laboratory to examine the investment responses to exogenous income shocks. 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. Using a similar event study framework, we analyze the response of investments in both crypto and traditional equity accounts out of this additional liquidity.

We find that investment in cryptocurrency increases following all three stimulus payments. As with temporary positive income shocks, the effects are most pronounced during the first two weeks after stimulus checks are received and are not significant in the following four weeks. Traditional investments exhibit similar patterns to crypto investments around stimulus payments. While the response of crypto and traditional investments to these exogenous income shocks is similar to our endogenous shocks, the magnitudes of the response are much higher following the stimulus checks. That said, while the magnitudes of the response of crypto investments to stimulus payments are significant and robust to a variety of specifications, they are economically 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 final piece of our analysis characterizes households' investment in the crypto market within a broader macroeconomic context. During the Covid-19 pandemic, supply chain disruptions and the adoption of unprecedented fiscal measures have pushed inflation concerns to the center of the policy debate. Cryptocurrencies—and especially Bitcoin—are commonly characterized as a hedge against inflation.[6] We make use of our rich set of transaction-level data to investigate how individual consumers view crypto investments in relation to their own experiences with inflation. We use recent local price changes across shopping categories and ex-ante consumption baskets (measured over the prior 12-months) to create individual-level proxies for inflation expectations. The changing prices of the particular 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 when gas and grocery prices have increased significantly in the recent past. The use of this investor-level measure has an additional advantage of allowing us to compare investors with similar incomes who reside in the same area but have different exposure to local inflation.

Using this individual-level measure, we find that households with higher inflation exposure increase their investment in cryptocurrency at both the extensive and intensive margins. The sensitivity of crypto investments to inflation exposure is more than seven times higher during the inflationary period after the Covid pandemic (2021–2023), consistent with consumers paying closer attention to inflation when the inflation level is high and thus returns

[6] E.g., see https://cointelegraph.com/learn/bitcoin-and-inflation-everything-you-need-to-know.

to hedging against inflation are also high (e.g., Katz, Lustig, and Nielsen, 2017; Sims, 2003). This effect is less pronounced for early crypto adopters but stronger for more sophisticated individuals, gamblers, and households that adopt crypto during the high-inflation period. We also find that this effect is particularly pronounced amongst consumers with more unstable incomes, but less so among those with more overall liquidity constraints. We find that traditional investments for both crypto and non-crypto investors respond positively to consumers' inflation expectations as well and much more so during the inflationary period. Although the absolute magnitudes of the response are smaller for non-crypto investors, the relative magnitudes are similar due to non-crypto investors investing less more generally. Combined, these results indicate that household liquidity and inflation concerns contribute to cryptocurrency investment as well as investment in traditional asset classes.

The literature surrounding cryptocurrency investments has been expanding rapidly. Some of these papers directly utilize blockchain 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 (2022) provide evidence of potential collusion among miners while other papers rely on surveys (e.g., Bohr and Bashir, 2014; Steinmetz, Von Meduna, Ante, and Fiedler, 2021; Auer and Tercero-Lucas, 2022; Candia, Coibion, Gorodnichenko, and Weber, 2023).

Some papers have investigated crypto markets under the lens of asset pricing. For instance, Liu and Tsyvinski (2021) show that cryptocurrency returns are driven by factors that are specific to cryptocurrency markets such as user adoption and the costs of cryptocurrency production. Liu, Tsyvinski, and Wu (2022) find that three factors—cryptocurrency market, size, and momentum—capture the cross-section of expected cryptocurrency returns. Kogan, Makarov, Niessner, and Schoar (2023) find that crypto investors have different beliefs about cryptocurrency price dynamics relative to other asset classes. 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, 2022). Hackethal, Hanspal, Lammer, and Rink (2022) find evidence of cryptocurrency investors holding other risky assets and being prone to biases in investment decision-making.

We contribute to this literature by analyzing the crypto market through the lens of retail investors allocating funds to this nascent asset class and provide the first large-scale characterization of investors. 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 increasing household liquidity were behind the crypto run-up in 2020 and later. Our analysis of the role inflation exposure has in crypto investment also builds on the literature studying how beliefs affect investors' expectations and portfolio choices. For instance, Giglio, Maggiori, Stroebel, and Utkus (2020) 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. Section I introduces the data and describes how the main variables in our analysis are computed. Section II presents several key facts about crypto investments that exploit the granularity of our data. Sections III and IV present the main findings about the role played by liquidity shocks and inflation expectations in driving crypto investments. Section V concludes.

I. Data

In this section, we describe our data sources, the process of identifying cryptocurrency transactions, and our key measures, such as the income shocks and the inflation exposure.

A. Transaction Level Data

Our main data source comprises de-identified transaction data from bank and credit card accounts for over 63 million U.S. consumers from January 2010 to June 2023. The data are unbalanced as consumers can enter and exit the panel. Still, we observe around 9.5 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 city and state of residence, from January 2014 to June 2023.

The data are proprietary and come from a large U.S. data aggregation and analytics platform. The data provider assists traditional financial institutions, including several top U.S. banks, as well as FinTech firms, 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. 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.

While our data are not a random subset of the U.S. consumers, our untabulated comparisons suggest that they are broadly representative of the general population across income (other than low-income unbanked consumers), spending patterns, and geography. Another common concern with these types of transaction-level data is that the data might not include all accounts for certain consumers, which means that we might not be able to observe the totality of income or spending by these consumers. To mitigate this concern and create a managible analysis sample, we follow the procedure in Aiello et al. (2023) to construct a random sample of investors for whom the data providers is more likely to have complete set of accounts based on the provider's data quality measure. Our results are robust to taking a random sample of the entire data set.[7]

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 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 February 2023, routed more than 62% of the transaction volume in the U.S. We thus can 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

[7] We refer to users in the data set as "investors" or "households" interchangeably. The data do not allow us to easily distinguish if members of the same household have joint or separate accounts.

contains such information in the description text field and all of these have Bitcoin or Ether as additional information when they do. We therefore assume that most of the transactions we are observing involve these two major cryptocurrencies, an assumption also consistent with Coinbase SEC disclosures related to their customers' aggregate crypto holdings.

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 equity brokerages, such as Charles Schwab, E*Trade, Vanguard and Fidelity, and collect information about deposits to and withdrawals from these accounts.

Using our transaction data set, we also create a number of 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). For example, we identify gamblers as consumers who ever transacted at casinos, lottery kiosks, play centers, or betting websites and are likely to be risk loving. We identify more sophisticated investors by flagging those who receive paycheck income from the top 200 finance firms. 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 and work experiences.

Table I presents the basic summary statistics. About 18% of individuals in our sample are crypto investors, while 63% invest post-tax dollars in brokerage accounts. A small fraction of people, about 7%, are employed by a financial institution. About 34% of individuals incurred at least one overdraft during our sample period, while about 10% are hand-to-mouth households. Finally, as a measure of risk aversion we are also able to identify the 29% of our sample that engage in gambling. Average monthly income and spending are approximately $10,800 and $8,400, respectively. On average, individuals in our sample make 3 crypto transactions, for a total of $1,400, and 26 transactions in their traditional accounts, for a total of $27,000. Crypto investors are higher income and tend to invest more in traditional markets than non-crypto investors and are more likely to be sophisticated and be gamblers.

C. Income Shocks

We use the information from transaction descriptions for deposits (i.e., credits) to identify instances in which the individuals experience abnormal income shocks. Income shocks are defined as weeks where the individual's salary is more (or less for negative shocks) than 0.5 standard deviations above the rolling 12-month salary average. In other words, let $s_{i,t}$ be the salary of individual i in week t, let $\sigma_{i,t-51,t}$ be the standard deviation of individual i's salary computed using salary data from week $t-51$ to week t (inclusive), and let $\mu_{i,t-51,t}$ be the average weekly salary for individual i from week $t-51$ to week t (inclusive). A positive income shock in week t for individual i is then defined as

$$\text{Positive Income Shock}_{i,t} = \mathbb{1}\{s_{i,t} > \mu_{i,t-51,t} + 0.5 \times \sigma_{i,t-51,t}\} \tag{1}$$

We also define a variable capturing whether the shocks are permanent or temporary in nature. Let $\sigma_{i,t+1,t+26}$ be the standard deviation of individual i's salary computed using salary data from week $t+1$ to week $t+26$ (inclusive), i.e. we are looking at six months ahead, and let $\mu_{i,t+1,t+26}$ be the average weekly salary for individual i from week $t+1$ to week $t+26$ (inclusive). A permanent positive income shock is a positive shock where the new level is within 0.5 standard deviations from the average weekly salary in the next 6 months and the future 6 month average is above the past 12 month average. A shock is temporary if it is not permanent.

This procedure allows us to identify both instances where individuals in our sample earn a large bonus, for instance, at the end of the year, as well as instances where they move to a higher paying job. These individual-specific shocks provide us with an opportunity to explore the extent to which the additional disposable income is used to invest in crypto. Negative income shocks are defined similarly.

We also augment the previous income shocks with 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 74,758 first-round stimulus payments, 59,314 second-round stimulus payments, and 72,886 third-round payments. There were fewer payments made during the second round of stimulus checks (Stimulus II), so we should expect a relatively smaller number of treated investors relative to Stimulus I and Stimulus III. Overall, the ability to observe the credits to individuals bank accounts provide us with a unique opportunity to explore the role of liquidity on the individuals' propensity to invest in the crypto markets.

D. Inflation Expectations

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 (2023) 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 category-level Consumer Price Index for All Urban Consumers (CPI) from 2010 to 2023 from the Bureau of Labor Statistics (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).[8] 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 and compute monthly realized inflation in each consumption category for each individual in our transaction data. We then annualize the monthly price changes. 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 because consumers observe these price changes most frequently and easily through their shopping behavior.[9] We measure these consumption baskets ex ante (over the preceding 12 months) because contemporaneous inflation can affect consumption, especially during economic downturns such as Covid-19 (e.g., see Cavallo, 2020). Our measure of inflation expectations has a positive correlation of 0.360 with a measure of

[8] 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 are 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`.

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

median expected price change over the following 12 months based on consumer surveys.[10]

Specifically, we measure investor-level inflation exposure (i.e., *Investor CPI*) as follows:

$$\textit{Investor CPI}_{it} = \frac{\sum_{c=1}^{n} \{\Delta_{1m,ann} CPI_{c,s,t} \times \omega_{c,i,t-1}\}}{\sum_{c=1}^{n} \omega_{c,i,t-1}}, \tag{2}$$

where $\Delta_{1m,ann} CPI_{c,s,t} = [CPI_{c,s,t}/CPI_{c,s,t-1}]^{12} - 1$ is the annualized 1-month change in the CPI in month t for consumption category c in state s, measured in decimal points, and $\omega_{c,i,t-1} = \sum_{k=t-12}^{t-1} X_{c,i,k}$ is the total expenditure in months $t-12$ to $t-1$ across consumption category c for individual i residing in state s.

The empirical advantage of this measure is that it varies both across time and across consumers, allowing for the inclusion of an interacted fixed effect for state, month, and income bracket in regression analysis. We can thus compare investors with similar income levels who reside in the same geography at the same time but have differential exposure to inflation due to differences in their consumption baskets. The underlying assumption behind this variation is that differential exposure to inflation is positively correlated with differences in inflation expectations, which these investors form, resulting in potentially different investment behaviour. We construct this measure for both crypto investors and non-crypto investors, for comparison.

II. 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 unique 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

We begin by describing when investors began to participate in the crypto market in relation to 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 Panel A plots the number of new cryptocurrency investors by month and overlays it with the annual Bitcoin return. The figure clearly shows that crypto markets during bull periods have resulted in new investors

[10]see the University of Michigan's Surveys of Consumers: Inflation Expectations at https://fred.stlouisfed.org/series/MICH.

joining the flock. At its peak in 2017–2018, there were more than 14 thousand new crypto investors per month within our sample population. During the latest boom there was a lower but more sustained surge in new investors, with around around 7 thousand per month joining the crypto market in the first half of 2021.

In Figure 1 Panel B, we plot the total monthly crypto investments and compare them to monthly traditional investments summed across the set of crypto investors in our sample. Similar to the pattern we observe for new crypto users, there is a significant spike in the amount of crypto investment during the first Bitcoin boom in 2017, when Bitcoin prices went from roughly \$2,000 to \$14,000. There is an even larger increase in crypto investment during the latest crypto boom in 2020–2021, when Bitcoin experienced a skyrocketing increase prices from \$10,000 to \$50,000, and a corresponding decline in the last part of our sample. Traditional investment seems to follow a somewhat different pattern, where there is a steady increase over most of our sample period and a decline starting in the second half of 2022.

While high returns appear to draw the attention of potential new crypto investors, in Figure 1 Panel C we find that large price spikes are also correlated with large amounts of crypto withdrawals, particularly during the first boom in 2017. At least some crypto investors appear to realize their crypto gains following periods of high returns. However, comparing the magnitudes across Panels B and C, we see that net deposits are increasing during crypto booms.

We further examine these withdrawal patterns by zooming in on the large withdrawal spike that occurs in late 2017 after the Bitcoin price first tops \$10,000. Specifically, we ask: Are these withdrawals primarily made by very early adopters who experienced all of this run-up, or are investors who experienced only a portion of this gain also exiting? Figure 2 plots net deposits to cryptocurrency exchanges in the months surrounding this Bitcoin run-up separately for households that first adopted crypto before 2017 and households that adopted crypto in 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 relatively newer adopters are depositing large amounts. A similar pattern is observed during the 2020 price spikes, with households experiencing large gains realizing a substantial fraction of them to deploy for consumption and investment in other assets (also see Aiello et al., 2023).

To put this investment activity into perspective, we scale the size of the crypto investment for the users we analyze by total income and total spending. Figure 3 shows that both during the earlier boom and in the latest part of our sample, the crypto investment share among cryptocurrency investors has approached its highest historical point, about 3% of total income and 4.5% of total spending.

We also illustrate the geographical distribution of the crypto investments. One might imagine that tech and financial hubs in the U.S. might be the places where crypto investment is concentrated. Figure 4 presents state-level maps of the U.S. reporting the number of new investors in crypto per 1,000 of households in our sample from 2015 to 2023. In the earliest years of crypto adoption, the concentration of new users was highest in the Rocky Mountain states, Iowa, Mississippi, and Vermont. By the 2017 Bitcoin price boom, new users had spread to the coasts and were particularly concentrated in California and New York. In contrast, during the most recent price run-up in 2021, new users were more evenly spread across the entire U.S.

B. *Crypto Investors vs. Non-Crypto Investors*

We also leverage the nature of our data to explore the distribution of crypto investments in our sample across other key individual financial characteristics. Figure 5 reports the percentage of investors by income class (computed in June 2023) for both the count and dollar volume of crypto transactions.[11] Panels A and B report these statistics separately for pre- and post-Covid adopters, defined based on whether their first transaction in crypto is earlier than 2020. Investors earning more than $75k are the most active, with individuals above this threshold making around 70% of the transactions. However, individuals earning less than $45k still make around 15% of the transactions. In terms of the dollar volume of transactions, 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 pre- and post-Covid crypto adopters. This evidence suggests that while wealthier investors tend to invest the largest amounts into cryptocurrency, lower-income individuals are still quite active participants in the market.

Columns 3–5 of Table I compare early adopters who first deposited to crypto exchanges prior to 2018, Covid adopters who first invested in 2020, and investors who first adopted during the high inflation period of 2021–2023. Column 6 reports average characteristics of non-crypto investors. Comparing across Columns 3 through 5, we see that the average income of crypto investors falls over time. While crypto adopters have more income than non-adopters, their overall spending patterns are quite similar. Aiello et al. (2023) show that there are no substantial differences in the amount of spending on auto, groceries, utilities, or medical expenses between crypto investors and non-investors. 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.

[11] We use income bracket information from the data provider, which assigns each user in each month to one of seven income brackets: $0–25k, $25–45k, $45–60k, $60–75k, $75–100k, $100–150k, and $150+k.

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 their transactions. For this sample, we compare zip code demographic characteristics.

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 higher percentage of immigrants (14.5% vs. 12.7% for non-adopters). Early crypto adopters also live in areas with a more educated population. For example, early crypto adopters live in zip codes where 25.2% of adults have a college degree and 17.6% have a graduate degree, whereas non-adopters live in zip codes where 23.9% and 16.3% have college and graduate degrees, respectively.

In Panel C of Table II, we explore differences in zip code size and income. Zip codes that early adopters come from are wealthier, with median annual household income about $4,000 higher than late adopters and non-adopters. Consistent with this finding, the fraction of people using food stamps is also lower in early adopters' areas. We report additional zip-level measures related to occupation and industry in Appendix Table IA.I. Overall, codes of crypto investors look similar to those of non-investors along most dimensions, with early crypto adopters tending to be more different than both later adopters and non-adopters.

C. *Crypto and Traditional Investments*

As a growing new asset class that exhibits limited correlation with existing assets such as equities or housing, cryptocurrency investment can be one component of a balanced investment portfolio. Furthermore, one might be concerned that investing in the crypto market, because of the allure of high returns, might come at the expense of lower investment in safer traditional markets. 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 deposits into brokerage accounts (ie. not investments withheld from paychecks), so we are only capturing active contributions and trading by investors rather than 401(k) automatic contributions.[12]

As a basic comparison, Figure 6 Panel A plots the median annual investment for crypto investors by income class for both crypto and traditional investments. We find that for crypto investors earning less than $75k, their investments in the crypto market and in post-tax brokerage accounts are quite comparable. These investments tend to be small, less than

[12] E.g., see Chetty, Friedman, Leth-Petersen, Nielsen, and Olsen (2014) for evidence of investor passivity with respect to automatic pension contributions in Denmark. Also see Dahlquist, Setty, and Vestman (2018).

$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 observable investment flows. For those earning between $100k and $150k, the crypto investment represents about half of their active after-tax traditional investments. The gap increases for those earning more than $150k, who tend to invest nearly five times more in stocks and bonds after tax than in cryptocurrencies.

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. Thus, lower-income households spend a much higher fraction of their investment money (and salaries) on crypto investment.

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 6 Panel B 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.

D. *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 investments, withdrawals, and net flows on contemporaneous and lagged Bitcoin 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:

$$\Delta y_t = \alpha_0 + \alpha_1 BTC\ Return_t + \alpha_2 BTC\ Return_{t-1} + \varepsilon_t, \tag{3}$$

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 Panel A. We observe a significant and positive relation between both gross investment and withdrawal flows with respect to Bitcoin prices, with a higher sensitivity of changes in withdrawals, suggesting that overall bullish and bearish market sentiment are a significant factor in driving crypto investment. Column 3 shows that overall net flows are positively significantly correlated with contemporaneous and lagged Bitcoin returns. In other words, crypto investors follow market momentum and invest more as returns improve, consistent with evidence in Liu et al. (2022).

We also test whether this same type of behavior is observed for their traditional investments. Table III Panel B performs a similar analysis for observable flows into traditional brokerage accounts and their relation with the S&P 500 return. In contrast to crypto, we do not find any significant relation between overall market conditions and investments (or net investments) in traditional markets, except for a smaller positive relation between withdrawals and contemporaneous market returns. 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 less responsive to overall market conditions.

III. Liquidity and Crypto Investing

Having established the key characteristics of crypto investors, and their differences with non-investors, we now turn to the analysis of how liquidity, i.e. an increase in disposable income, affects the propensity to invest in crypto.

A. Crypto Investing around Income Shocks

The granularity of our data allows us to identify instances where individuals receive an income shock, defined as a sudden change in disposable income which might correspond to a bonus, a large lump sum payment, a promotion, or job loss. Positive (negative) income shocks are defined as weeks where an individual's salary is more (less) than 0.5 times the rolling 12-month salary standard deviation above the rolling 12-month salary average. We also differentiate between permanent and temporary income shocks. A permanent income shock is a shock where the new income level stays the same in the next 6 months (see Section I.C). Exploring the investment propensity around these events provides an opportunity to better understand how factors related to cash flow and income deferentially impact investors' portfolio choices.

Table IV reports the results for responses in cryptocurrency and traditional investments and withdrawals to positive (Panel A) and negative (Panel B) income shocks, respectively. The after-shock variable summarizes the weeks around the window into one indicator where 1 represents weeks 0 to 1 after the shock and 0 represents weeks -6 to -1 and weeks 2 to 6. Columns 1 and 3 report the coefficients for the subsample of permanent shocks, and

Columns 2 and 4 report the estimates for the subsample of temporary shocks. To capture differences across individuals, we include person fixed effects, as well as week by state by income class fixed effects, which ensure that other time varying shocks at the regional or income class level do not confound our estimates. Panel A shows that for both crypto and traditional investments, individuals react to positive income shocks by increasing their financial exposures. This is true for both permanent and temporary shocks, but the economic magnitudes of the effects are larger for temporary shocks. In contrast, Panel B shows that investors withdraw from both markets in response to negative income shocks. However, they do so only in response to temporary shocks.

We next graphically examine the weekly investment patters for the crypto and traditional investments before and after the income shocks. Specifically, we estimate the following regression at the calendar week level and plot the β coefficients separately for each type of shock:

$$y_{it} = \alpha_{it} + \sum_{k=-6}^{6} \beta_k \mathbb{1}\{Income\ Shock - t = k\} \times T_{it} + \varepsilon_{it}, \tag{4}$$

where y_{it} represents the log dollar amount of investment in crypto or traditional asset classes. $T_{it} = 1$ for the $+/-6$ week window around the income shocks and $T_{it} = 0$ for a random $+/-6$ week period in the past, before the income shock, for a given retail investor.

We include investor and 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 cluster standard errors at the investor level.

Figure 7 reports the weekly coefficients β_k from Equation (4). Whereas for crypto investment there is a clear pattern where the coefficient is indistinguishable from zero in the weeks preceding the shock and then spikes for both permanent and temporary shocks in the week of the shock and the week after, we find a more cyclical pattern for traditional investments. The reason is likely due to the bi-weekly deposits of salary income for some consumers (the spikes occur every two weeks) and automatic investments into brokerage accounts, which are widespread for traditional investment but are not present for crypto. Indeed, the spikiness in investments in weeks surrounding positive income shocks other than the week of the shock itself practically disappears when we restrict the sample to users who do not have frequent annual traditional deposits, defined as investors not in the top quartile of the number of deposits per year (Appendix Figure IA.I). As shown in Table IV, temporary negative income shocks lead to an increase in both crypto and traditional withdrawals, while the permanent ones do not. We observe the same pattern graphically in Figure 7. Lastly, we find that the effects of income shocks on traditional investments are similar for crypto investors and non-crypto investors (Appendix Figure IA.II).

Overall, it seems that there is a significant response of crypto investment to a sudden increase in disposable income. While we observe these income shocks across the entire sample period, at least some of these changes in income may be endogenous to investing or anticipated. The next section exploits another source of income shocks, the stimulus payments during the Covid-19 crisis, to estimate the marginal propensity to invest in that setting. These stimulus check payments provide a source of exogenous increase in income that is likely transitory in nature.

B. *Crypto Investing around Stimulus Payments*

The significant spike in crypto sector investments in early 2020, which we document earlier, 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. We complement the previous section by using this policy shock as a natural experiment about liquidity and investment behavior.

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 in April 2020 (Stimulus I), the second 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.[13] Given the large 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 in both cryptocurrencies as well as traditional investments before and after these additional funds are received.

We use the staggered timing of the arrival of stimulus payments in retail investors' bank

[13] In all cases, this aid started phasing out at $75,000 for single individuals and $150,000 for couples.

accounts as a source of quasi-exogenous variation in liquidity available for investing. Table V Panel A reports the results of regressing crypto investments on the interaction term between the window around stimulus payments and an indicator for weeks 0 and 1 after these checks were deposited in consumer accounts, similar to the specification in Table IV. Of note, our stringent week by state by income class fixed effects are essential to absorb time trends because the increase in crypto investments might mirror an overall increase in risk-taking appetite resulting from the low interest rate environment during Covid-19 together with the increased possibility for investors to spend time at home monitoring their portfolios.

Columns 1, 2, and 3 of Table V report the results separately for each round of stimulus. We find that crypto investments are higher in the first two weeks after stimulus payments we made, suggesting that a (small) portion of the financial aid provided by the government was invested in crypto. This result corroborates survey evidence in Coibion, Gorodnichenko, and Weber (2020) who find that consumers mostly saved their stimulus money or paid down debts from these transfers. These findings are also consistent with indirect evidence in Divakaruni and Zimmerman (2023), which shows an increase in crypto investing around the receipt of stimulus checks. However, we find much smaller magnitudes of the effects compared to Divakaruni and Zimmerman (2023), suggesting that a large portion of stimulus money possibly went to consumption, as intended by policy-makers.

A natural question is whether the crypto investment reacts differently to the stimulus checks than the traditional investments do or whether these deposits were simply a part of an increase in overall investment behavior following the stimulus. To test if this is the case, we examine the response of traditional investment to the stimulus checks. Table V Panel B reports the effects of stimulus payments on traditional investments. Very much like crypto investments, traditional investments increase in the two weeks surrounding stimulus payments for Stimulus I and III. The coefficients are about twice the size of those for crypto investments. The negative coefficient for Stimulus II appears at odds with these results. However, upon further investigation, we find that the negative coefficient is entirely driven by a more gradual increase in traditional investments after this round, which peak in weeks 3 to 6 after the payment, reversing the coefficient. We show this graphically below.

We next graphically examine the pattern of crypto and traditional investments relative to the stimulus date in an event study framework, differentiating between the three different stimulus rounds. Specifically, we estimate the following regression at the calendar week level and plot the β coefficients separately for each round:

$$y_{it} = \alpha_{it} + \sum_{k=-6}^{6} \beta_k \mathbb{1}\{Stimulus - t = k\} \times T_{it} + \varepsilon_{it}, \tag{5}$$

where y_{it} represents the log dollar amount invested in crypto or traditional assets. $T_{it} = 1$ 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.[14] As with other income shocks, we include investor and state of residence by income class by week fixed effects α_{it}. As above, we cluster standard errors at the investor level.

We plot the coefficients of interest β_k from Equation (5) estimated for Stimulus I, along with 95% confidence intervals around them, in Figure 8. Consistent with regression evidence, we observe a statistically significant spike in crypto investment in the week of stimulus payment. This increase in crypto investing subsides in the following six weeks after the payment date, similarly to the effects of temporary income shocks reported in Figure 7. It is noteworthy that we see no statistically distinguishable run-up in crypto investing before the stimulus week. The absence of pre-trends gives us comfort in interpreting the relation between stimulus payments and crypto investing as likely causal. Likewise, we find a similar sharp increase in the amount of traditional investment in the stimulus week (see Figure 8). However, this increase in traditional investments drops somewhat more abruptly than that for crypto investments.

We reproduce plots in Figure 8 for the other two rounds of stimulus checks in Appendix Figure IA.III. The effects on crypto investing are less pronounced for Stimulus II but larger for Stimulus III. We also observe that the levels drop much more rapidly in the weeks after the next two rounds of stimulus payments compared to Stimulus I payments. These results suggest that 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), whereas the effects of the following rounds are more 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 decline. The spike for traditional investments during the second round happens in weeks 3 to 6 after the stimulus week, which suggests that retail investors might favor investing excess liquidity in the crypto market before considering traditional asset classes. We also find very similar response of traditional investments to stimulus payments for crypto investors versus non-crypto investors, suggesting that these two groups of investors are not as different as some would think (Appendix Figure IA.IV).

[14] 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 possible clustering of stimulus payments around certain calendar weeks in the data.

IV. Inflation and Crypto Investing

In this section, we explore how consumer expectations regarding 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 1982.[15] This dramatic increase in CPI-U resulted in significant and ongoing concerns about the impact of the rising prices 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 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 (2023) 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 frameworks, 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 against price increases. 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. Additionally, expectations of future inflation might increase retail investor risk aversion, inducing them to sell assets such as cryptocurrencies, which are very volatile, and

[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 tightened 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.

[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.

buy more 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 et al., 2023), 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 cryptocurrencies 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 persistent levels of high inflation.

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 patterns. 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 et al., 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. Crypto Investment Response to Investor-Level Inflation

We start by exploring the relation between crypto investing and investor-level inflation exposure (*Investor CPI*). This strategy allows us to investigate 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

[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 Bitcoin growth rate is stable in the short-run.

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 report the baseline results for our sample of crypto users in Table VI. Columns 1 and 2 report the results of regressing crypto investments on investor-level inflation exposure, while Columns 3 and 4 provide the effect on traditional investments as a benchmark. We control for investor and state by income class by month fixed effects. We find that increases in investor inflation exposure are positively related to crypto investment (Column 1) and this result is even more pronounced—it is indeed more than seven times larger—during periods of high inflation (Column 2). The magnitude is economically significant. A one percentage point increase in the annual investor-level CPI inflation is 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. These results hold for the extensive margin of crypto investing. Consumers increase their likelihood to invest in crypto in response to higher inflation expectations, especially when inflation is high (Columns 1 and 2 of Appendix Table IA.IV).

It is useful to compare the response of crypto investments to inflation to that of 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 measure of investor-level inflation in Columns 3 and 4 of Table VI. We find similar results. The coefficients of individual exposure to inflation are positive and statistically significant, consistent with the results on crypto investing (Column 3). This is also true for the interaction with the inflationary periods (Column 4). The results are robust to the extensive margin of traditional investing (Columns 3 and 4 of Appendix Table IA.IV). We also examine whether the results change when we remove investing through FinTech brokerages (e.g., Robinhood, Acorns) from the definition of traditional investing because many FinTech brokerages launched crypto investing options in the last several years of our sample period.[18] Our results hold (Appendix Table IA.V).

In supplementary analysis, we compare the response of traditional investments by crypto investors to those by non-crypto investors. We reproduce the results for crypto investors in

[18]See U.S. crypto user surveys in "Cryptocurrency exchanges used by consumers in the United States from 2021 to 2023," *Measure Protocol*, May 2, 2023.

Columns 1 and 2 of Appendix Table IA.VI. Columns 3 and 4 report the results for non-crypto investors. We find generally similar effects with coefficients that are about twice smaller for non-investors. One should keep in mind, however, that non-crypto investors are typically less likely to invest in traditional asset classes and invest smaller amounts when they do (see Table I), which means that the economic magnitudes of the effects in percentage terms are comparable across the two sets of investors.[19] We examine heterogeneity in the effects we find next.

C. *Heterogeneous Response of Crypto Investment to Inflation*

The effects of inflation on cryptocurrency investing are likely heterogeneous. We thus examine differential responses of crypto investing 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 investor-level inflation exposure (*Investor CPI*) with proxies for these investor traits. Of note, the coefficients of the level of *Investor CPI* remain positive and significant after we include these interactions.

Increased levels of financial sophistication could lead to increased awareness of the hedging properties inherent in cryptocurrency relative to say stocks or bonds (or lack of such properties) and the availability of other tools to hedge inflation. 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. 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 three 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.[20] We find that early adopters of crypto invest significantly less in crypto when their inflation exposure increases. One interpretation of this result is that the 2017 Bitcoin market collapse could have altered these investors' risk

[19] We find mixed results when we interact inflation exposure with two measures of changes in consumer sentiment (Appendix Table IA.VII).

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

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) and Andersen, Hanspal, and Nielsen (2019). Adding the coefficient of the level and the interaction term results in a negative sum (1.397-1.897=-0.5), suggesting withdrawal of money from the crypto market by early investors with rising inflation exposure.[21] Column 4 reports the results for heterogeneity based on a dummy for consumers who invested in crypto for the first time during Covid (*Covid Adopter*), while Column 5 focuses on those becoming crypto adopters during the high inflation period (*High Inflation Adopter*). We find positive and statistically significant coefficients of the interaction terms for both consumers who adopted crypto during the Covid-related economic downturn and those who adopted crypto during 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 remains positive and statistically significant, similarly to that for crypto investments. Therefore, the same investors are more likely to invest in both crypto and traditional securities such as stocks and bonds when inflation increases. The interaction terms load similarly to those in Panel A of Table VII, with the exception of gamblers and Covid adopters who tend to invest somewhat less in traditional securities when they are more exposed to inflation. The results are broadly similar when we restrict the sample to the inflationary period (Appendix Table IA.VIII).

The results in Table VIII reveal heterogeneity in the effect across retail investors by the severity of their budget constraints. Columns 1–3 of Panel A examine whether the effect of inflation expectations on crypto investment differs by investor financial constraints as captured by their income, by whether they have ever incurred an overdraft, and by whether they are hand-to-mouth households. 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 price 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, Columns 1–3 show that the elasticity of crypto investments with respect to inflation expectations does not seem to depend on consumers' constraints. If anything,

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

being a hand-to-mouth consumer makes it less likely to react to inflation by investing in crypto. However, we document in Column 4 that higher variability in salary income is positively related to crypto investing when inflation exposure is high. We find similar results for the interaction between inflation expectations and having an unstable salary on crypto investments when we restrict the sample to the inflationary period (Appendix Table IA.IX Panel A).

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 less positively to inflation exposure for low-income investors, overdrafters, and hand-to-mouth consumers. By contrast, high salary volatility investors are more likely to increase their traditional investments in response to inflation. These results hold during the inflationary period (Appendix Table IA.IX Panel B). Overall, our findings suggest that investors likely do consider cryptocurrencies as an inflation hedge, at par with traditional securities.

V. 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 crypto trading information due to anonymous nature of wallet addresses, we use detailed bank account transactions for a representative sample of U.S. consumers. The advantage of our data is that they offer both information about deposits to and withdrawals from crypto accounts at centralized exchanges like Coinbase and information about crypto investors' (and non-investors') other transactions such as income and spending. We exploit the fact that we observe a detailed picture of the investors' finances to investigate how individuals' characteristics, liquidity, and inflation expectations drive the propensity to invest in crypto and traditional asset classes.

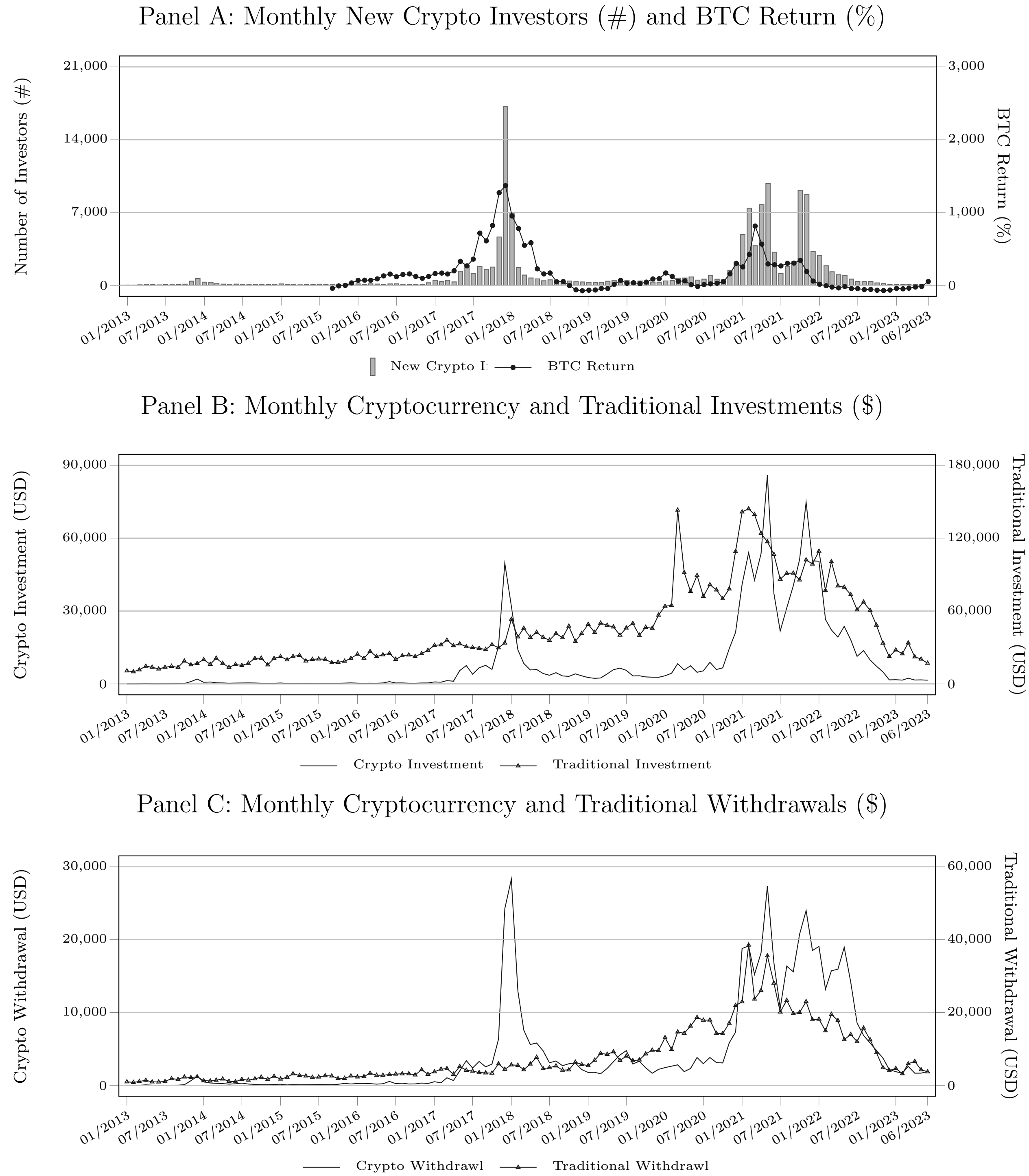
We start by examining the characteristics of crypto investors and the evolution of retail crypto investing. We document significant interest by retail investors in crypto during booms in Bitcoin prices in 2017 and 2020–2021. We relate crypto investing to the Bitcoin returns over time. We show that investors' deposits to and withdrawals from the crypto exchanges are positively and significantly correlated with Bitcoin 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 momentum pattern in crypto suggests that retail investors' adoption of this new technology has been significantly influenced by the cryptocurrencies price appreciation. We also show that wealthier individuals are more likely to invest in the crypto market, especially among early crypto adopters. However, investors are distributed across the income spectrum and have been significantly more widespread across the U.S. in the latest boom cycle. Finally, we show that more financially sophisticated individuals and gamblers are more likely to be crypto investors.

We next examine several potential drivers of crypto investing. First, we examine whether liquidity shocks, in the form of significant changes in income or stimulus check payments, can explain the increase in interest in the crypto market. Indeed, temporary positive income shocks are followed by a spike in crypto investing around the shock, while permanent positive income shocks have a lasting positive impact on crypto investing. While we find that investors did invest a fraction of their additional disposable income into crypto, these amounts totaled only a small portion of overall crypto investment in recent years. In addition, investors behavior is mostly comparable between crypto and traditional markets.

Finally, we provide evidence that inflation expectations are positively correlated with crypto investing. We construct a measure of consumer-level exposure to inflation based on their personal 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 and those with less stable income, providing some evidence that crypto may be seen as one potential hedge against the rise of inflation.

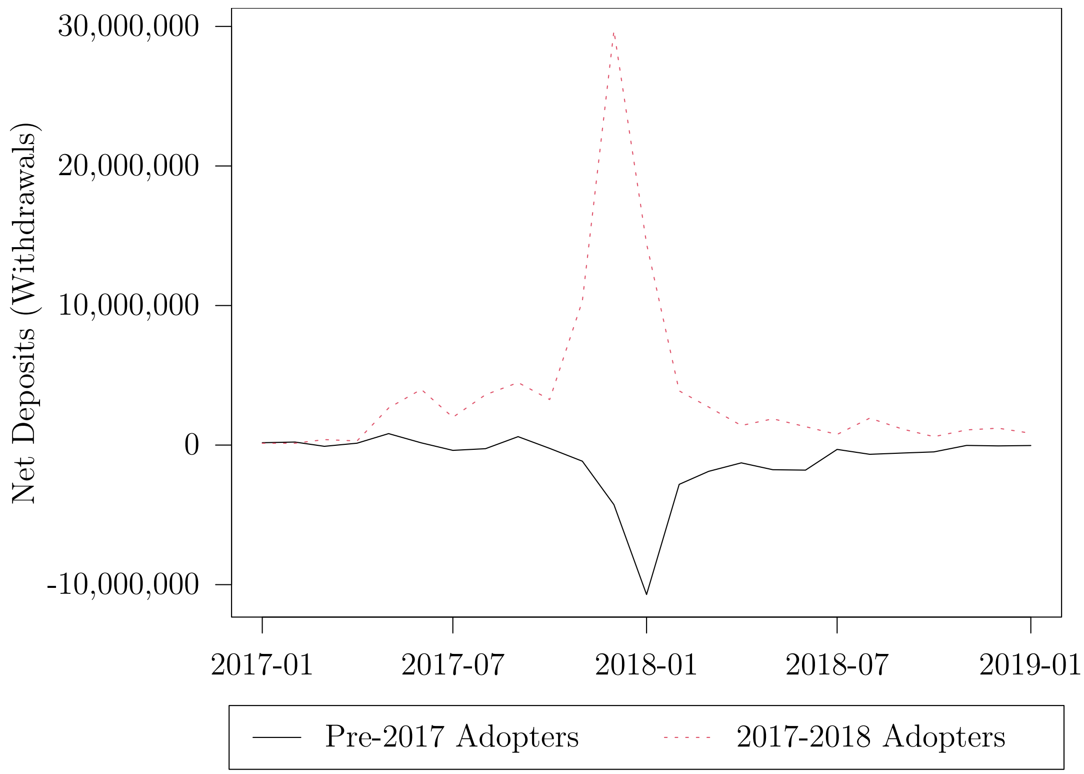
Our results point to that crypto investors are not as dissimilar from equity investors as some might believe. Importantly for policy makers, the excitement of the last several years around this new asset class did not seem to come at the expenses of investments in more traditional assets.

Figure 1. Crypto and Traditional Investment Dynamics



This figure displays the relationship between cryptocurrency retail investment flows and BTC dynamics for crypto investors. Panel A plots monthly new cryptocurrency investors amount vis-à-vis BTC returns and S&P 500. Panel B plots monthly dollar cryptocurrency investment amount vis-à-vis traditional investment amount. Panel C plots monthly dollar cryptocurrency investment withdrawal amount vis-à-vis traditional investment withdrawal amount.

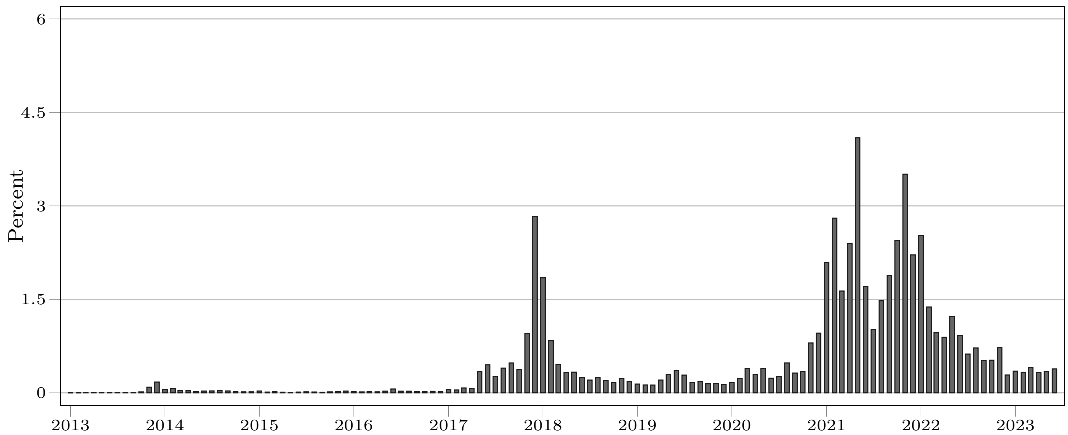
Figure 2. Net Deposits (Withdrawals) by Crypto Adoption Cohort



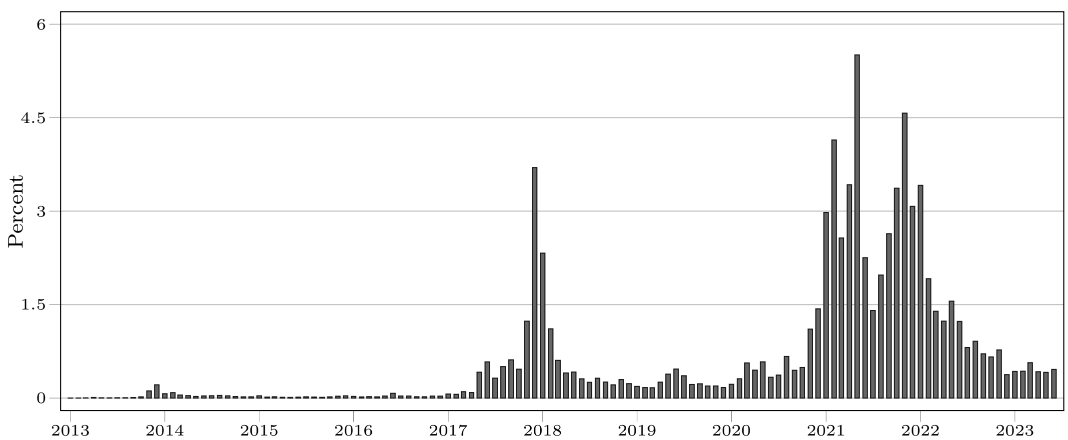
This figure plots net deposits to (and net withdrawals from) cryptocurrency exchanges, splitting the sample into those who first interacted with an exchange prior to or after 2017. We note substantial net withdrawals from exchanges by pre-2017 adopters and substantial net deposits from those adopting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

Figure 3. Crypto Investment Share

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

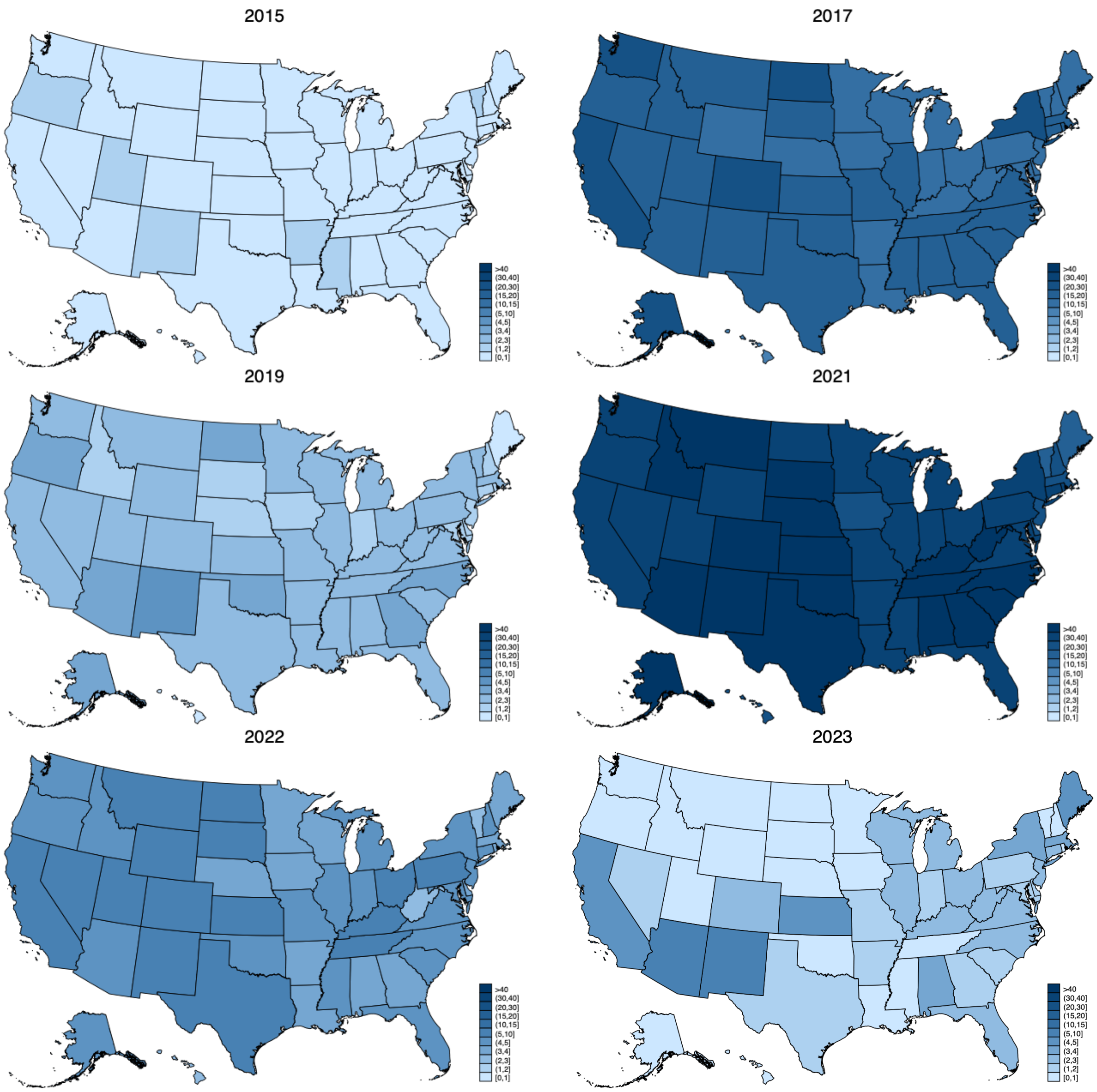


Panel B: Monthly Cryptocurrency Investment as a Percentage of Total Spending



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

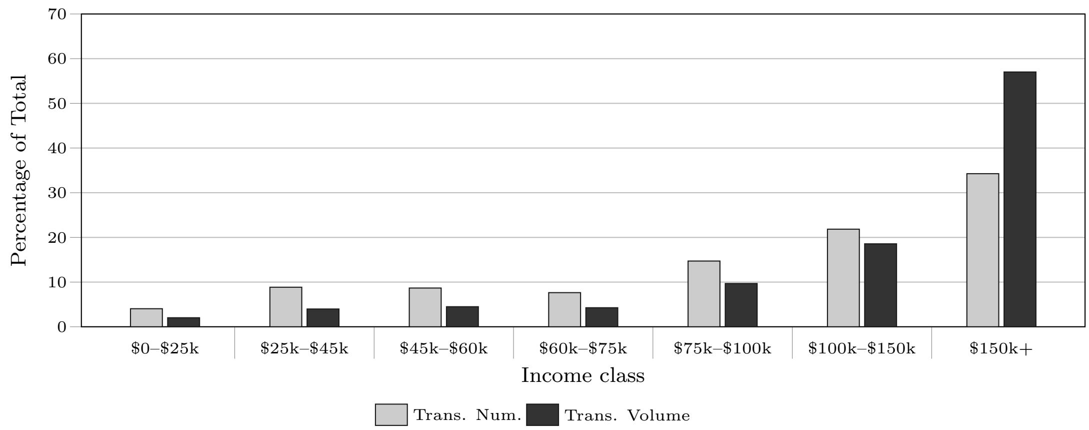
Figure 4. New Cryptocurrency Investors per 1,000 Households, as of June 2023



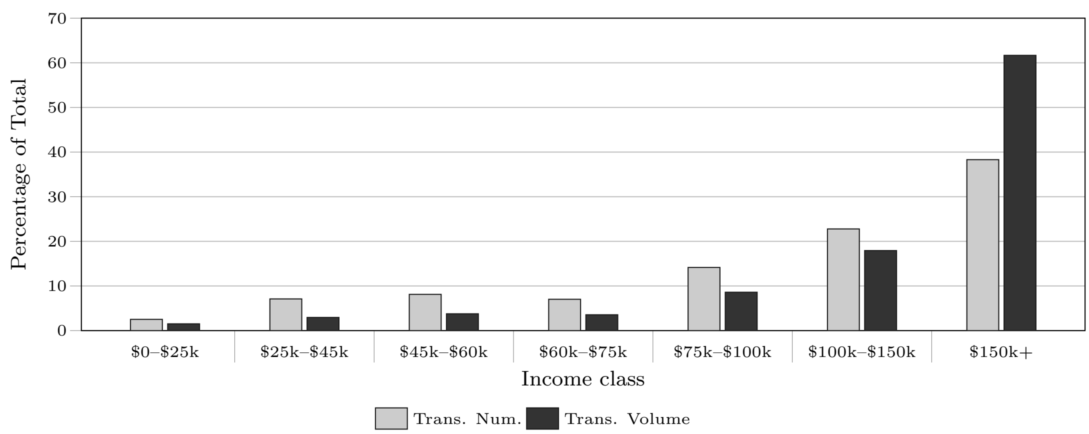
This figure illustrates the number of new cryptocurrency investors scaled by the number of households (in thousand) for different states in the U.S. from 2015 to 2023. The number of 2023 investors is scaled up by a factor of 365/178 to account for our sample ending on June 28, 2023 rather than the end of year.

Figure 5. Percentage of Investors by Income Class, as of June 2023

Panel A: Pre-Covid Adopters



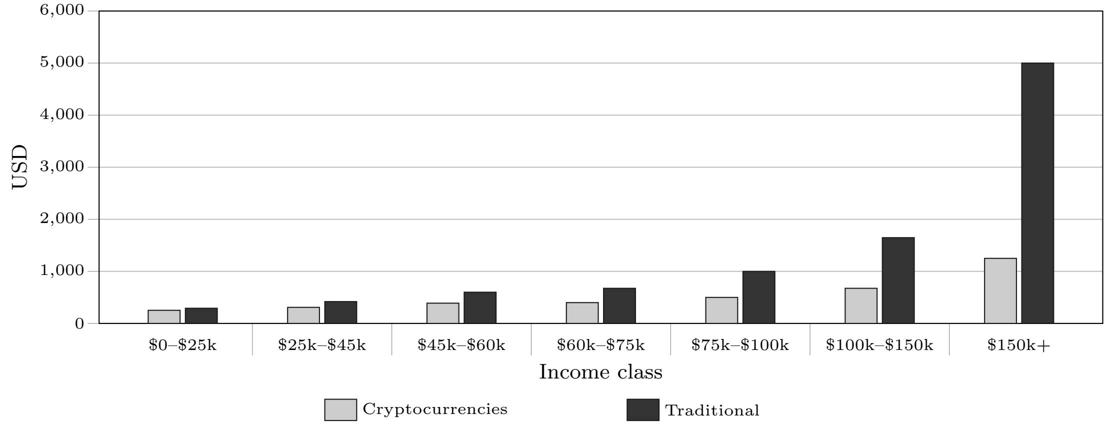
Panel B: Post-Covid Adopters



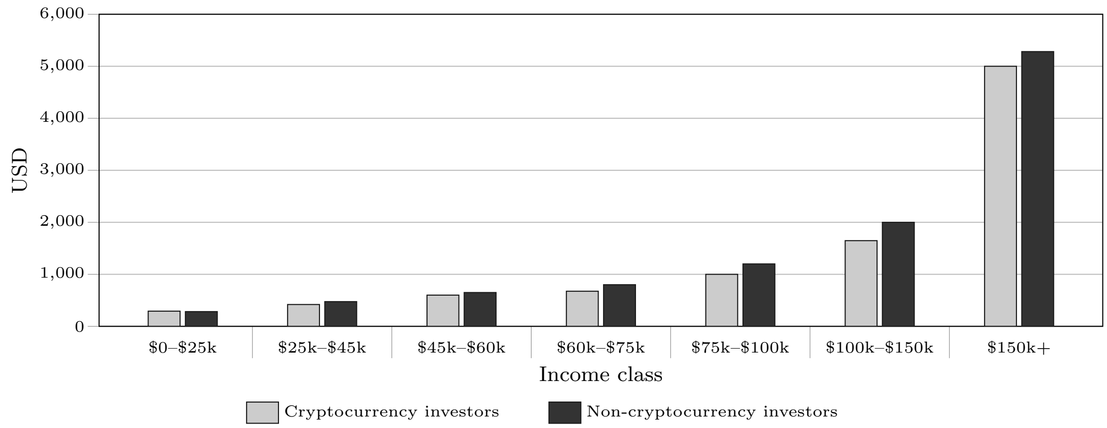
This figure displays the distribution of cryptocurrency investment across income classes by number of transactions and dollar volume. Panel A plots the distribution of cryptocurrency investment by income class for cryptocurrency investors who began investing in crypto prior to Covid (pre-2020). Panel B plots the distribution of cryptocurrency investment by income class for cryptocurrency investors who began investing in crypto after Covid (2020–2023).

Figure 6. Median Annual Investment by Income Class, as of June 2023

Panel A: Investment by Asset and Income Class

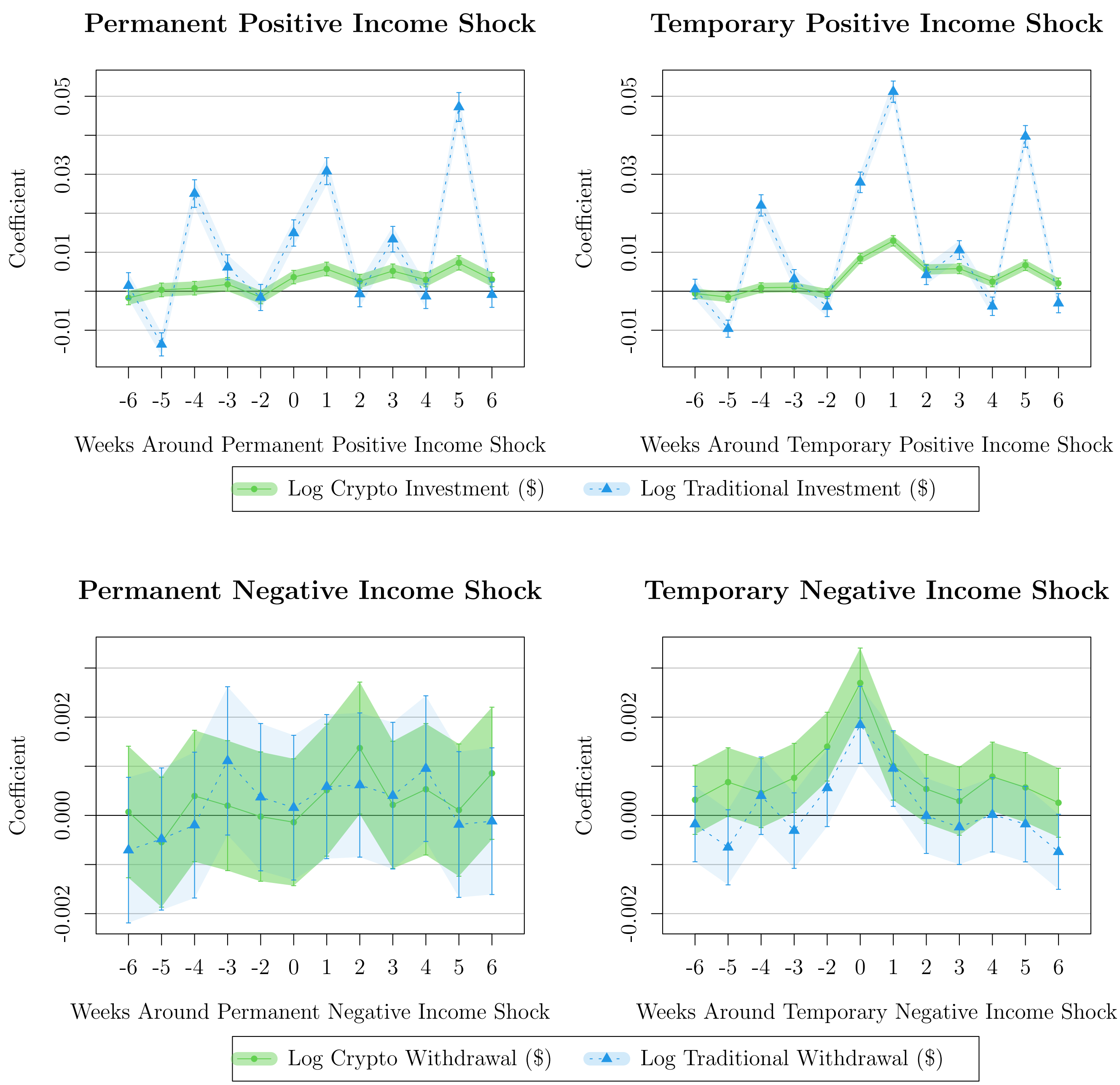


Panel B: Traditional Investment: Crypto v. Non-Crypto Investors



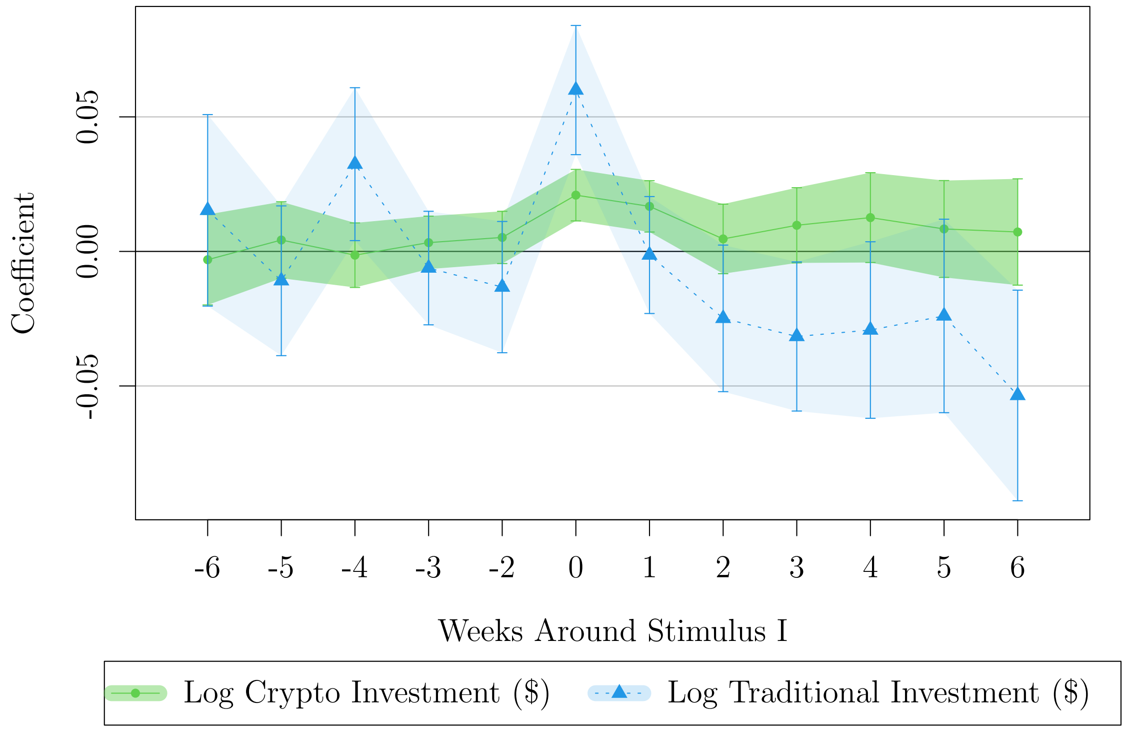
This figure plots median annual investment in crypto and traditional assets by income class. Panel A displays the distribution of traditional investment and cryptocurrency investment across asset and income classes by dollar volume for cryptocurrency investors. Panel B displays the distribution of traditional investment across income classes by dollar volume for cryptocurrency and non-cryptocurrency investors.

Figure 7. Retail Investment and Withdrawal Responses after Income Shocks



These figures display the difference in cryptocurrency and traditional investment and withdrawal before v. after a positive and negative income shock. All figures plot β_k from Equation (4) for the log dollar amount invested and withdrawn in either asset class.

Figure 8. Retail Investment Responses after Stimulus I



This figure displays the difference in cryptocurrency and traditional investment before v. after receiving the first stimulus check. The figure plots β_k from Equation (5) for the log dollar amount invested in either asset class.

Table I. Summary Statistics

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 in the year 2020. The fifth column displays summary statistics for crypto investors who began investing after January 2021. The sixth column reports summary statistics for non-crypto investors. The definitions of variables are provided in Appendix Table IA.X.

		Full Sample	Crypto Investors	Crypto Adoption			Non-Crypto Investors
				Early	Covid	High Inflation	
Panel A: Investor Characteristics							
Likelihood of Being Crypto Investor	(%)	17.50	100.00	100.00	100.00	100.00	0.00
Likelihood of Being Traditional Investor	(%)	63.43	80.22	81.35	81.48	79.54	59.87
Likelihood of Being Sophisticated	(%)	7.12	10.39	13.26	10.36	8.72	6.42
Likelihood of Ever Below-Median Income	(%)	48.69	43.56	42.77	45.71	43.61	49.78
Likelihood of Ever Using Overdrafts	(%)	33.86	32.42	35.17	31.98	30.31	34.16
Likelihood of Ever Gambling	(%)	28.70	38.80	38.27	39.36	39.11	26.56
Likelihood of Ever Being Hand-to-Mouth	(%)	9.70	7.09	5.50	8.21	7.83	10.25
Panel B: Income, Spending & Investing							
Total Income	($)	10,819	11,974	13,213	11,797	11,223	10,570
Salary Income	($)	4,575	4,919	5,094	4,801	4,824	4,500
Total Spending	($)	8,380	9,041	10,001	8,925	8,446	8,240
Crypto Investment Transactions	(#)	3	20	28	29	14	0
Crypto Investment Transactions	($)	1,426	8,147	12,872	13,299	4,849	0
Traditional Investment Transactions	(#)	26	37	39	38	35	23
Traditional Investment Transactions	($)	26,711	36,409	45,789	39,058	31,182	24,654
N		812,530	142,188	39,589	9,990	74,012	670,342

Table II. Zip Demographics

This table shows sample means of zip code-level characteristics based on the imputed home zip code of investors. Note that we only identify zip codes for 80% of users. Data are based on a user-level panel of weekly transaction data. Early adopters are defined as first investing in crypto before January 2018. Covid adopters are individuals who first invested in crypto in the calendar year of 2020. High-inflation adopters are defined as first investing in crypto after January 2021. Non-crypto investors do not use crypto during our sample period of 2014–2023.

	Full Sample	Crypto Investors	Crypto Adoption			Non-Crypto Investors
			Early	Covid	High Inflation	
Panel A: Race and Ethnicity						
% White	74.3	73.4	72.8	72.9	74.0	74.4
% Black	13.4	13.7	13.2	14.5	13.9	13.4
% Asian	7.0	7.4	8.5	7.1	6.8	7.0
% Other	5.2	5.4	5.5	5.4	5.3	5.2
% Hispanic	15.5	16.1	16.1	16.0	16.0	15.3
% Immigrant	12.8	13.2	14.5	12.9	12.4	12.7
Panel B: Education						
Median Age	38.4	37.9	37.9	38.0	38.0	38.5
% Male	49.3	49.4	49.4	49.4	49.4	49.3
% Military	1.2	1.4	1.3	1.5	1.6	1.2
% Less than High School	8.1	8.1	7.9	8.2	8.2	8.1
% High School/Some College	51.7	51.4	49.2	52.1	52.6	51.8
% College	23.9	24.1	25.2	23.7	23.5	23.9
% Grad School	16.3	16.4	17.6	16.0	15.7	16.3
Panel C: Zip Size and Income						
Population	36,001	36,645	36,792	36,737	36,466	35,865
Pop. Density	3,281	3,478	4,213	3,296	3,064	3,239
Median Household Income	81,206	81,563	84,295	80,883	80,030	81,131
% Foodstamps	7.7	7.7	7.3	7.8	7.9	7.7

Table III. Investment Flows in Response to Prices

This table reports OLS estimates of changes in types of retail investment to changes in asset prices (see Equation (3)). Panel A reports estimates of changes in retail crypto investment to changes in Bitcoin prices. Panel B reports estimates of changes in retail traditional brokerage investment to changes in S&P 500 prices. The data consist of monthly percentage changes from January 2013 to June 2023. The percentage change in retail crypto (traditional) investment is defined as the percentage change in the monthly sum of all deposits to cryptocurrency exchanges (traditional retail brokerages) across all people in our dataset. Changes in withdrawals are defined in an analogous way based on withdrawals from crypto exchanges and retail brokerages. Column 1 reports estimates of the effect of prices on investment, Column 2 shows estimates of the effect on withdrawals, and Column 3 reports estimates of the effect on net investment (e.g., deposits less withdrawals). In both panels, the percentage changes are in decimal form. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *t*-statistics are presented in parentheses.

Panel A: Cryptocurrency Investment Flows in Response to BTC Return

	Dependent variable		
	% Chg Investments (1)	% Chg Withdrawals (2)	% Chg Net Investments (3)
BTC Return (%)	0.984***	1.862***	0.611***
	(13.818)	(2.881)	(3.162)
Lag(BTC Return (%), 1)	0.501***	1.057	0.437**
	(3.539)	(1.473)	(2.397)
Constant	0.041	0.027	0.218
	(1.281)	(0.380)	(1.122)
N	126	126	126
R-squared	0.53	0.41	0.03

Panel B: Traditional Investment Flows in Response to S&P 500 Return

	Dependent variable		
	% Chg Investments (1)	% Chg Withdrawals (2)	% Chg Net Investments (3)
S&P 500 Return (%)	−0.593	0.459**	−0.856
	(−0.757)	(1.961)	(−0.896)
Lag(S&P 500 Return (%), 1)	0.135	0.607	−0.020
	(0.290)	(1.605)	(−0.035)
Constant	0.018	0.008	0.024
	(1.090)	(0.842)	(1.156)
N	126	126	126
R-squared	0.03	0.03	0.04

Table IV. Investment and Withdrawal Response to Income Shocks

This table reports the difference in cryptocurrency and traditional investment and withdrawal before v. after a positive and negative income shock. The window around shock is the T_{it} variable is equation (3), and the after shock variable summarizes the weeks around the window into one indicator where 1 represents weeks 0 to 1 after the shock and 0 represents weeks -6 to -1 and weeks 2 to 6. Columns 1 and 3 report the coefficients for the subsample of permanent shocks, and columns 2 and 4 report the estimates for the subsample of temporary shocks. The estimates of the intercept and fixed effects are omitted for brevity. 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.

Panel A: Positive Income Shocks and Investment

	Log Crypto Investment ($)		Log Traditional Investment ($)	
	(1)	(2)	(3)	(4)
Window Around Shock (1/0) × After Shock Weeks (1/0)	0.0034***	0.0092***	0.0180***	0.0354***
	(5.692)	(20.72)	(17.44)	(42.02)
Shock Type	Permanent	Temporary	Permanent	Temporary
N	13,932,433	25,877,239	13,932,433	25,877,239
R-squared	0.14	0.12	0.20	0.18
Person FE	Yes	Yes	Yes	Yes
Week × State × Income Class FEs	Yes	Yes	Yes	Yes

Panel B: Negative Income Shocks and Withdrawal

	Log Crypto Withdrawal ($)		Log Traditional Withdrawal ($)	
	(1)	(2)	(3)	(4)
Window Around Shock (1/0) × After Shock Weeks (1/0)	-8.72×10^{-6}	0.0015***	0.0003	0.0015***
	(-0.0183)	(5.864)	(0.5165)	(5.541)
Shock Type	Permanent	Temporary	Permanent	Temporary
N	7,374,773	23,598,802	7,374,773	23,598,802
R-squared	0.09	0.05	0.09	0.06
Person FE	Yes	Yes	Yes	Yes
Week × State × Income Class FEs	Yes	Yes	Yes	Yes

Table V. Investment Response to Stimulus Checks

This table reports the difference in cryptocurrency and traditional investment before v. after the three stimulus checks. The window around shock is the T_{it} variable is equation (3), and the after shock variable summarizes the weeks around the window into one indicator where 1 represents weeks 0 to 1 after the shock and 0 represents weeks -6 to -1 and weeks 2 to 6. Column 1 corresponds to stimulus I. Column 2 corresponds to stimulus II. Column 3 corresponds to stimulus III. The estimates of the intercept and fixed effects are omitted for brevity. 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.

Panel A: Log Crypto Investment ($)

	Stimulus I	Stimulus II	Stimulus III
	(1)	(2)	(3)
Window Around Shock (1/0) × After Shock Weeks (1/0)	0.0133***	0.0178**	0.0476***
	(4.784)	(2.401)	(6.610)
N	1,931,890	1,524,378	1,885,002
R-squared	0.24	0.21	0.23
Person FE	Yes	Yes	Yes
Week × State × Income Class FEs	Yes	Yes	Yes

Panel B: Log Traditional Investment ($)

	Stimulus I	Stimulus II	Stimulus III
	(1)	(2)	(3)
Window Around Shock (1/0) × After Shock Weeks (1/0)	0.0450***	-0.0208**	0.0729***
	(7.894)	(-2.361)	(9.126)
N	1,931,890	1,524,378	1,885,002
R-squared	0.25	0.24	0.25
Person FE	Yes	Yes	Yes
Week × State × Income Class FEs	Yes	Yes	Yes

Table VI. Retail Investment Response to Inflation Exposure

This table reports the estimates of the response of cryptocurrency and traditional investment to investor-level inflation exposure for crypto investors. Columns 1–2 report the estimates of crypto investment response to inflation exposure. Columns 3–4 report the estimates of traditional investment response to inflation exposure. The estimates of the intercept and fixed effects are omitted for brevity. 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.

	Log Crypto Investment ($)		Log Traditional Investment ($)	
	(1)	(2)	(3)	(4)
Investor CPI	0.8608***	0.2438***	1.510***	0.0931**
	(26.88)	(11.58)	(32.52)	(2.259)
Investor CPI × Inflationary Period (1/0)		1.541***		3.538***
		(19.88)		(33.38)
N	14,781,679	14,781,679	14,781,679	14,781,679
R-squared	0.19	0.19	0.41	0.41
Person FEs	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

Table VII. Heterogeneous Response to Inflation Exposure – Risk Attitude & Experience

This table reports the estimates of the heterogeneous response of the cryptocurrency investment (Panel A) and traditional investment (Panel B) to investor-level inflation exposure based on investors' risk attitude and experience. Column 1 reports the estimates based on investor sophistication (*Sophisticated*). Column 2 reports the estimates based on propensity to gamble (*Gambler*). Column 3 reports the estimates based on early adoption of cryptocurrency (*Early Adopter*). Column 4 reports the estimates based on crypto adoption during Covid (*Covid Adopter*). Column 5 reports the estimates based on crypto adoption during high-inflationary period (*High Inflation Adopter*). The estimates of the intercept and fixed effects are omitted for brevity. 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.

Panel A: Crypto Investment

	Log Crypto Investment ($)				
	(1)	(2)	(3)	(4)	(5)
Investor CPI	0.7764***	0.7738***	1.397***	0.7731***	0.3025***
	(23.65)	(21.51)	(39.97)	(23.79)	(7.481)
Investor CPI × Sophisticated (1/0)	0.8067***				
	(10.06)				
Investor CPI × Gambler (1/0)		0.2403***			
		(5.269)			
Investor CPI × Early Adopter (1/0)			-1.897***		
			(-37.18)		
Investor CPI × Covid Adopter (1/0)				1.597***	
				(13.47)	
Investor CPI × High Inflation Adopter (1/0)					1.077***
					(24.05)
N	14,781,679	14,781,679	14,781,679	14,781,679	14,781,679
R-squared	0.19	0.19	0.19	0.19	0.19
Person FEs	Yes	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes	Yes

Panel B: Traditional Investment

	Log Traditional Investment ($)				
	(1)	(2)	(3)	(4)	(5)
Investor CPI	1.122***	1.578***	1.565***	1.518***	1.315***
	(23.56)	(30.78)	(31.25)	(32.29)	(23.68)
Investor CPI × Sophisticated (1/0)	3.698***				
	(30.04)				
Investor CPI × Gambler (1/0)		-0.1885***			
		(-3.051)			
Investor CPI × Early Adopter (1/0)			-0.1961***		
			(-2.914)		
Investor CPI × Covid Adopter (1/0)				-0.1590	
				(-1.228)	
Investor CPI × High Inflation Adopter (1/0)					0.3756***
					(6.265)
N	14,781,679	14,781,679	14,781,679	14,781,679	14,781,679
R-squared	0.41	0.41	0.41	0.41	0.41
Person FEs	Yes	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes	Yes

Table VIII. Heterogeneous Response to Inflation Exposure – Budget Constraints

This table reports the estimates of the heterogeneous response of the cryptocurrency investment (Panel A) and traditional investment (Panel B) to investor-level inflation exposure based on investors' budget constraints. Column 1 reports the estimates based on income level (*Below-Median Income*). Column 2 reports the estimates based on consumer ever incurring an overdraft (*Overdrafter*). Column 3 reports the estimates based on bring hand-to-mount investor (*Hand-to-Mouth*). Column 4 reports the estimates based on investors' 12-month normalized salary volatility (*Salary Volatility*). The estimates of the intercept and fixed effects are omitted for brevity. 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.

Panel A: Crypto Investment

	Log Crypto Investment ($)			
	(1)	(2)	(3)	(4)
Investor CPI	0.8421***	0.8412***	0.8764***	0.7988***
	(20.24)	(23.34)	(26.11)	(17.92)
Investor CPI × Below-Median Income (1/0)	0.0361			
	(0.7484)			
Investor CPI × Overdrafter (1/0)		0.0549		
		(1.166)		
Investor CPI × Hand-to-Mouth (1/0)			-0.1394*	
			(-1.790)	
Salary Volatility				-0.0014
				(-0.5857)
Investor CPI × Salary Volatility				0.2137***
				(3.720)
N	14,781,679	14,781,679	14,781,679	11,872,455
R-squared	0.19	0.19	0.19	0.21
Person FEs	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

Panel B: Traditional Investment

	Log Traditional Investment ($)			
	(1)	(2)	(5)	(4)
Investor CPI	1.695***	1.650***	1.616***	1.555***
	(28.36)	(31.55)	(33.53)	(24.25)
Investor CPI × Below-Median Income (1/0)	-0.3580***			
	(-5.572)			
Investor CPI × Overdrafter (1/0)		-0.3938***		
		(-6.282)		
Investor CPI × Hand-to-Mouth (1/0)			-0.9508***	
			(-11.96)	
Salary Volatility				-0.0202***
				(-4.178)
Investor CPI × Salary Volatility				0.2404***
				(3.192)
N	14,781,679	14,781,679	14,781,679	11,872,455
R-squared	0.41	0.41	0.41	0.42
Person FEs	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

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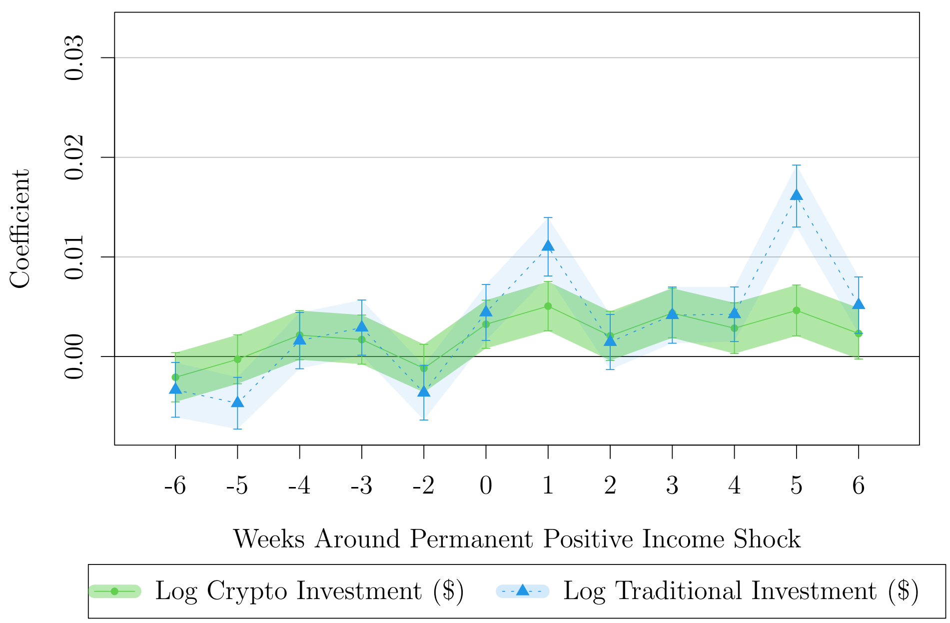
Internet Appendix to "Cryptocurrency Investing: Stimulus Checks and Inflation Expectations"

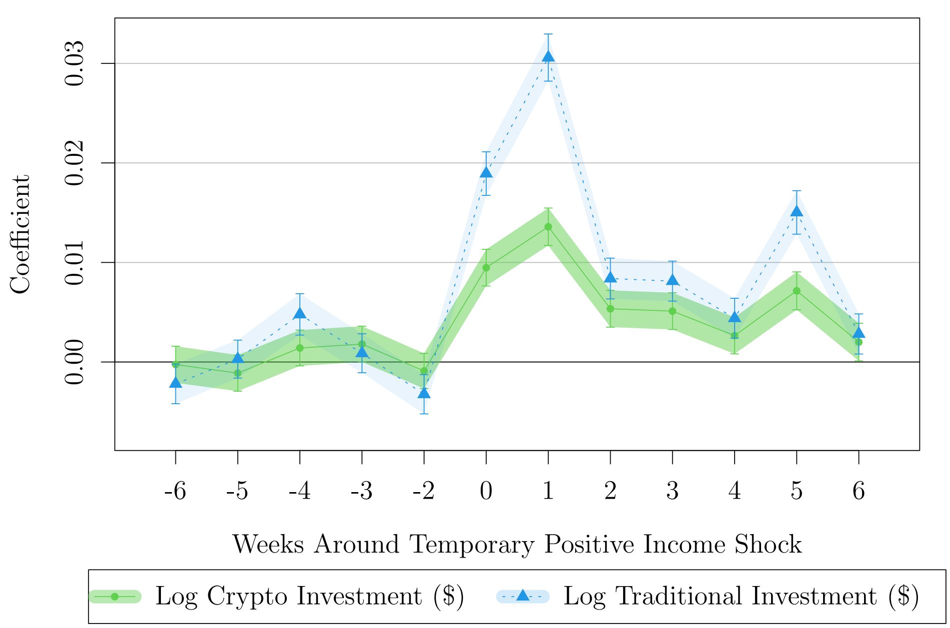
FOR ONLINE PUBLICATION

Figure IA.I. Retail Investment Responses after Income Shocks – Excluding Frequent Traditional Investors

Panel A: Retail Investment Responses After Permanent Positive Income Shocks

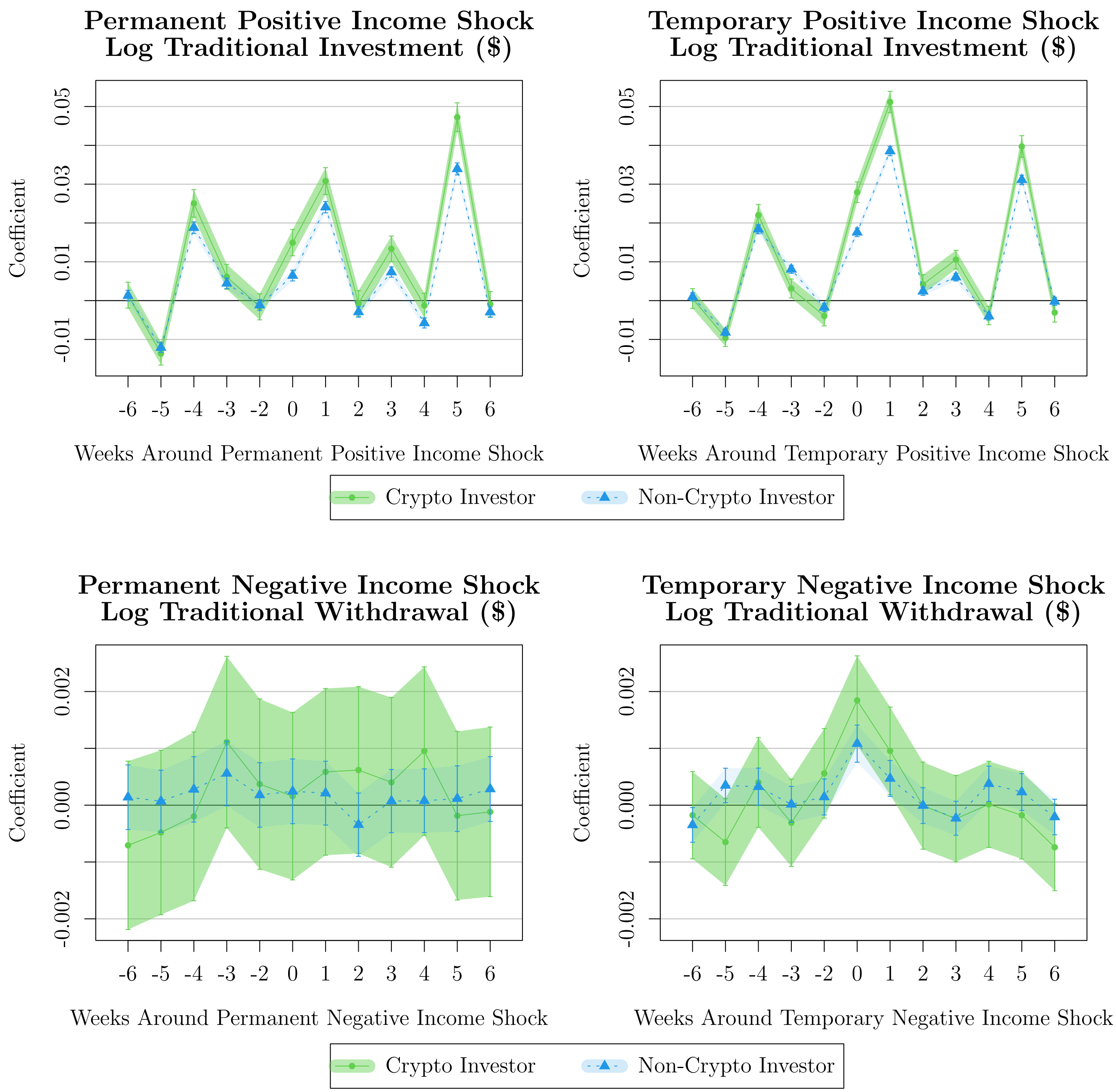


Panel B: Retail Investment Responses After Temporary Positive Income Shocks



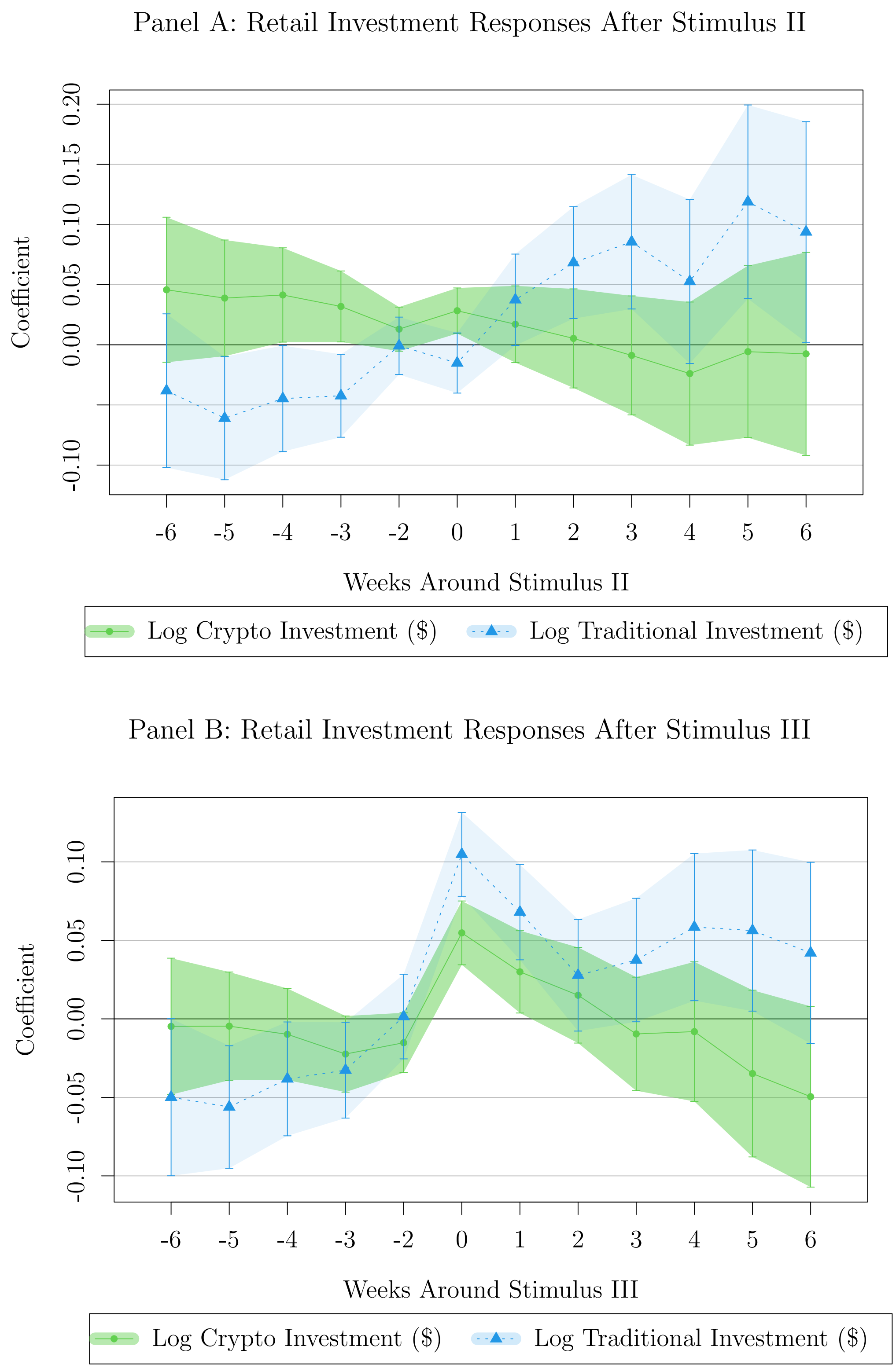
These figures display the difference in cryptocurrency and traditional investment before v. after positive income shocks for users who do not have frequent annual traditional deposits, defined as those investors not in the top quartile of the number of deposits per year. All figures plot β_k from Equation (4) for the log dollar amount invested and withdrawn in either asset class.

Figure IA.II. Traditional Investment Responses after Income Shocks – Crypto Investors vs. Non-Crypto Investors



These figures display the difference in traditional investment and withdrawal before v. after a positive and negative income shock for crypto and non-crypto investors. All figures plot β_k from Equation (4) for the log dollar amount invested and withdrawn in the traditional asset class.

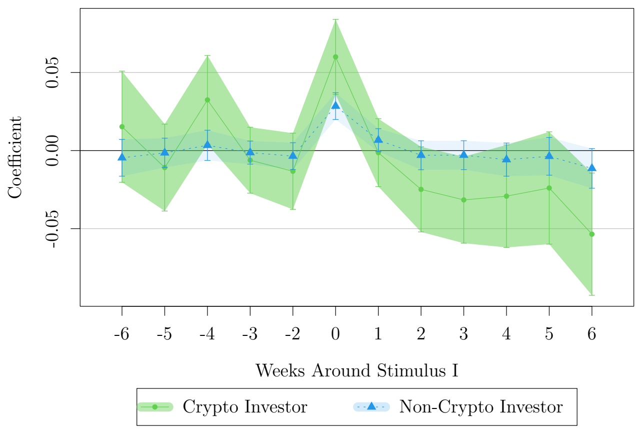
Figure IA.III. Retail Investment Responses after Stimulus Checks



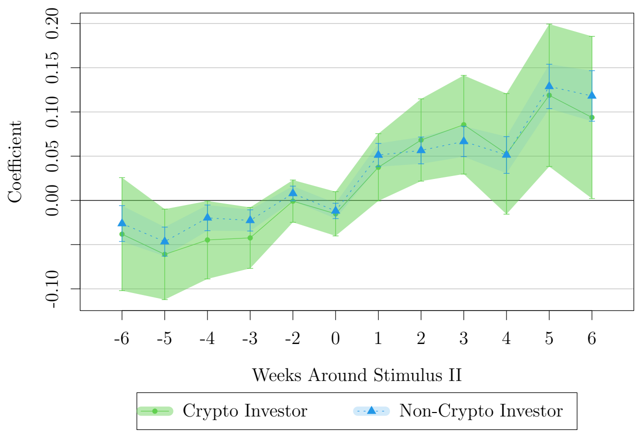
These figures display the difference in cryptocurrency and traditional investment before v. after receiving the second and third stimulus check. The figure plots β_k from Equation (5) for the log dollar amount invested in either asset class.

Figure IA.IV. Traditional Investment Responses after Stimulus Checks – Crypto Investors vs. Non-Crypto Investors

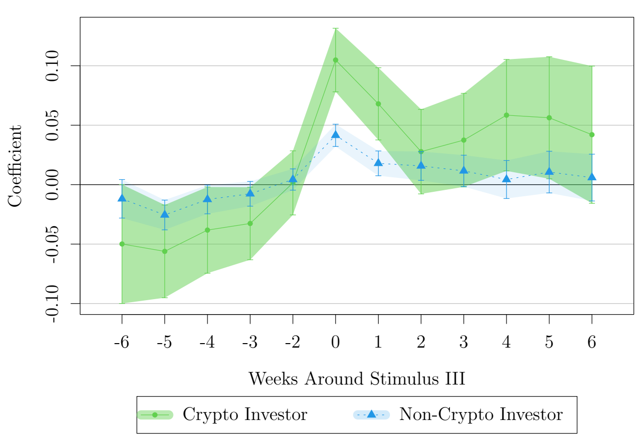
Panel A: Retail Traditional Investment Response After Stimulus I



Panel B: Retail Traditional Investment Response After Stimulus II



Panel C: Retail Traditional Investment Response After Stimulus III



These figures display the difference in traditional investment before v. after the second and third stimulus check for crypto and non-crypto investors. All figures plot β_k from Equation (5) for the log dollar amount invested in the traditional asset class.

Table IA.I. Zip Demographics – Occupation & Industry

This table shows sample means of zip code-level occupation and industry characteristics based on the imputed home zip code of users, and extends the summary statistics in Table II. Data are based on a user-level panel of weekly transaction data. Early adopters are defined as first investing in crypto before January 2018. Covid adopters are individuals who first invested in crypto in the calendar year of 2020. High-inflation adopters are defined as first investing in crypto after January 2021. Non-crypto investors do not use crypto during our sample period of 2014–2023.

	Full Sample	Crypto Investors	Crypto Adoption			Non-Crypto Investors
			Early	Covid	High Inflation	
Panel A: Zip Occupation						
% Managerial/Professional	44.4	44.6	46.3	44.1	43.7	44.4
% Services	16.1	16.2	15.8	16.3	16.4	16.1
% Sales/Office	21.0	21.0	20.7	21.1	21.1	21.0
% Farming	0.3	0.3	0.3	0.3	0.3	0.3
% Construction	7.0	7.0	6.6	7.1	7.2	7.0
% Transportation	11.1	10.9	10.3	11.1	11.3	11.2
Panel B: Zip Industry						
% Agriculture	1.0	1.0	0.9	1.0	1.0	1.0
% Construction	6.0	6.0	5.8	6.1	6.1	6.0
% Manufacturing	8.8	8.5	8.3	8.5	8.7	8.9
% Wholesale Trade	2.3	2.3	2.3	2.3	2.3	2.3
% Retail Trade	10.9	10.9	10.6	10.9	11.0	10.9
% Transportation	5.2	5.2	5.0	5.3	5.3	5.2
% Information	2.0	2.1	2.2	2.0	2.0	2.0
% Finance	7.3	7.3	7.6	7.2	7.1	7.3
% Professional	13.3	13.5	14.3	13.3	13.0	13.2
% Education/Health	23.6	23.4	23.4	23.4	23.5	23.6
% Recreation	9.3	9.5	9.5	9.5	9.5	9.3
% Other	4.7	4.7	4.6	4.7	4.7	4.7
% Public Admin.	5.6	5.8	5.6	5.9	5.9	5.6
% Self-employed	5.4	5.4	5.5	5.4	5.4	5.4

Table IA.II. Investment and Withdrawal Likelihood Response to Income Shocks

This table reports the difference in cryptocurrency and traditional investment and withdrawal likelihood before v. after a positive and negative income shock. The window around shock is the T_{it} variable is equation (3), and the after shock variable summarizes the weeks around the window into one indicator where 1 represents weeks 0 to 1 after the shock and 0 represents weeks -6 to -1 and weeks 2 to 6. Columns 1 and 3 report the coefficients for the subsample of permanent shocks, and columns 2 and 4 report the estimates for the subsample of temporary shocks. The estimates of the intercept and fixed effects are omitted for brevity. 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.

Panel A: Positive Income Shocks and Investment Likelihood

	Crypto Investment Likelihood (1/0)		Traditional Investment Likelihood (1/0)	
	(1)	(2)	(3)	(4)
Window Around Shock (1/0) × After Shock Weeks (1/0)	0.0006***	0.0013***	0.0031***	0.0051***
	(5.962)	(16.53)	(17.17)	(36.39)
Shock Type	Permanent	Temporary	Permanent	Temporary
N	13,932,433	25,877,239	13,932,433	25,877,239
R-squared	0.15	0.13	0.20	0.18
Person FE	Yes	Yes	Yes	Yes
Week × State × Income Class FEs	Yes	Yes	Yes	Yes

Panel B: Negative Income Shocks and Withdrawal

	Crypto Withdrawal Likelihood (1/0)		Traditional Withdrawal Likelihood (1/0)	
	(1)	(2)	(3)	(4)
Window Around Shock (1/0) × After Shock Weeks (1/0)	6.33×10^{-6}	0.0003***	0.0001	0.0003***
	(0.0809)	(6.607)	(1.254)	(5.407)
Shock Type	Permanent	Temporary	Permanent	Temporary
N	7,374,773	23,598,802	7,374,773	23,598,802
R-squared	0.09	0.05	0.08	0.05
Person FE	Yes	Yes	Yes	Yes
Week × State × Income Class FEs	Yes	Yes	Yes	Yes

Table IA.III. Traditional Non-FinTech Investment and Withdrawal Response to Income Shocks

This table reports the difference in traditional brokerage investment and withdrawal before v. after a positive and negative income shock. The window around shock is the T_{it} variable is equation (3), and the after shock variable summarizes the weeks around the window into one indicator where 1 represents weeks 0 to 1 after the shock and 0 represents weeks -6 to -1 and weeks 2 to 6. Column 1 report the coefficients for the subsample of permanent shocks, and column 2 report the estimates for the subsample of temporary shocks. The estimates of the intercept and fixed effects are omitted for brevity. 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.

Panel A: Positive Income Shocks and Investment

	Log Traditional Non-FinTech Investment ($)	
	(1)	(2)
Window Around Shock (1/0) × After Shock Weeks (1/0)	0.0178***	0.0350***
	(17.31)	(41.81)
Shock Type	Permanent	Temporary
N	13,932,433	25,877,239
R-squared	0.19	0.18
Person FE	Yes	Yes
Week × State × Income Class FEs	Yes	Yes

Panel B: Negative Income Shocks and Withdrawal

	Log Traditional Non-FinTech Withdrawal ($)	
	(1)	(2)
Window Around Shock (1/0) × After Shock Weeks (1/0)	-0.0003	0.0009***
	(-0.6665)	(4.236)
Shock Type	Permanent	Temporary
N	7,374,773	23,598,802
R-squared	0.10	0.06
Person FE	Yes	Yes
Week × State × Income Class FEs	Yes	Yes

Table IA.IV. Retail Investment Likelihood Response to Inflation Exposure

This table reports the estimates of the response of cryptocurrency and traditional investment likelihood to investor-level inflation exposure for crypto investors. Columns 1–2 report the estimates of crypto investment likelihood response to inflation exposure. Columns 3–4 report the estimates of traditional investment likelihood response to inflation exposure. The estimates of the intercept and fixed effects are omitted for brevity. 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.

	Crypto Investment Likelihood (1/0)		Traditional Investment Likelihood (1/0)	
	(1)	(2)	(3)	(4)
Investor CPI	0.1635***	0.0349***	0.2775***	0.0383***
	(30.58)	(9.881)	(36.27)	(5.528)
Investor CPI × Inflationary Period (1/0)		0.3212***		0.5974***
		(24.87)		(34.31)
N	14,781,679	14,781,679	14,781,679	14,781,679
R-squared	0.19	0.19	0.40	0.40
Person FEs	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

Table IA.V. Traditional Non-FinTech Investment Response to Inflation Exposure

This table reports the estimates of the response of traditional non-FinTech investment to investor-level inflation exposure for crypto investors. Columns 1–2 report the estimates of traditional non-FinTech investment amount response to inflation exposure. Columns 3–4 report the estimates of traditional non-FinTech investment likelihood response to inflation exposure. The estimates of the intercept and fixed effects are omitted for brevity. 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.

	Log Traditional Non-FinTech Investment ($)		Traditional Non-FinTech Investment Likelihood (1/0)	
	(1)	(2)	(3)	(4)
Investor CPI	1.454***	0.0992**	0.2615***	0.0373***
	(31.65)	(2.428)	(35.17)	(5.499)
Investor CPI × Inflationary Period (1/0)		3.384***		0.5602***
		(32.33)		(33.16)
N	14,781,679	14,781,679	14,781,679	14,781,679
R-squared	0.41	0.41	0.40	0.40
Person FEs	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

Table IA.VI. Traditional Investment Response to Inflation Exposure – Crypto Investors vs. Non-Crypto Investors

This table compares the estimates of the response of traditional investment to investor-level inflation exposure for crypto and non-crypto investors. Columns 1–2 report the estimates of traditional investment response to inflation exposure for crypto investors. Columns 3–4 report the estimates of traditional investment response to inflation exposure for non-crypto investors. The estimates of the intercept and fixed effects are omitted for brevity. 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.

	Log Traditional Investment ($)			
	Crypto Investors		Non-Crypto Investors	
	(1)	(2)	(3)	(4)
Investor CPI	1.510***	0.0931**	0.8875***	0.1541***
	(32.52)	(2.259)	(56.47)	(10.91)
Investor CPI × Inflationary Period (1/0)		3.538***		1.883***
		(33.38)		(52.18)
N	14,781,679	14,781,679	68,268,302	68,268,302
R-squared	0.41	0.41	0.48	0.48
Person FEs	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

Table IA.VII. Retail Investment Response to Inflation Exposure & Consumer Sentiment

This table reports the estimates of the response of cryptocurrency and traditional investment to investor-level inflation exposure interacted with consumer sentiment for crypto investors. Columns 1 and 3 report the results for the monthly change in the University of Michigan Consumer Sentiment Index. Columns 2 and 4 report the results for the monthly change in the Conference Board Consumer Confidence Index. The estimates of the intercept and fixed effects are omitted for brevity. 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.

	Log Crypto Investment ($)		Log Traditional Investment ($)	
	(1)	(2)	(3)	(4)
Investor CPI	0.8840***	0.8637***	1.469***	1.521***
	(28.04)	(26.92)	(31.68)	(32.70)
Investor CPI × Chg Consumer Sentiment	1.592***		-2.349***	
	(3.818)		(-4.034)	
Investor CPI × Chg Consumer Confidence		1.696***		6.484***
		(5.341)		(12.69)
N	14,750,468	14,781,679	14,750,468	14,781,679
R-squared	0.19	0.19	0.41	0.41
Person FEs	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

Table IA.VIII. Heterogeneous Response to Inflation Exposure During Inflationary Period – Risk Attitude & Experience

This table reports the estimates of the heterogeneous response of the cryptocurrency investment (Panel A) and traditional investment (Panel B) to investor-level inflation exposure during inflationary period based on investors' risk attitude and experience. Column 1 reports the estimates based on investor sophistication (*Sophisticated*). Column 2 reports the estimates based on propensity to gamble (*Gambler*). Column 3 reports the estimates based on early adoption of cryptocurrency (*Early Adopter*). Column 4 reports the estimates based on crypto adoption during Covid (*Covid Adopter*). Column 5 reports the estimates based on crypto adoption during high-inflationary period (*High Inflation Adopter*). The estimates of the intercept and fixed effects are omitted for brevity. 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.

Panel A: Crypto Investment

	Log Crypto Investment ($)				
	(1)	(2)	(3)	(4)	(5)
Investor CPI	1.695***	1.692***	1.976***	1.764***	1.193***
	(25.80)	(24.82)	(29.14)	(26.99)	(16.77)
Investor CPI × Sophisticated (1/0)	0.4839***				
	(4.888)				
Investor CPI × Gambler (1/0)		0.1520***			
		(2.673)			
Investor CPI × Early Adopter (1/0)			-0.8263***		
			(-13.63)		
Investor CPI × Covid Adopter (1/0)				-0.3056**	
				(-2.250)	
Investor CPI × High Inflation Adopter (1/0)					1.053***
					(19.24)
N	3,115,598	3,115,598	3,115,598	3,115,598	3,115,598
R-squared	0.35	0.35	0.35	0.35	0.35
Person FEs	Yes	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes	Yes

Panel B: Traditional Investment

	Log Traditional Investment ($)				
	(1)	(2)	(3)	(4)	(5)
Investor CPI	2.194***	2.310***	2.342***	2.333***	2.339***
	(31.37)	(31.35)	(32.42)	(33.03)	(30.50)
Investor CPI × Sophisticated (1/0)	1.364***				
	(11.51)				
Investor CPI × Gambler (1/0)		0.0844			
		(1.480)			
Investor CPI × Early Adopter (1/0)			-0.0062		
			(-0.0950)		
Investor CPI × Covid Adopter (1/0)				0.1301	
				(1.071)	
Investor CPI × High Inflation Adopter (1/0)					0.0014
					(0.0243)
N	3,115,598	3,115,598	3,115,598	3,115,598	3,115,598
R-squared	0.59	0.59	0.59	0.59	0.59
Person FEs	Yes	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes	Yes

Table IA.IX. Heterogeneous Response to Inflation Exposure During Inflationary Period – Budget Constraints

This table reports the estimates of the heterogeneous response of the cryptocurrency investment (Panel A) and traditional investment (Panel B) to investor-level inflation exposure during inflationary period based on investors' budget constraints. Column 1 reports the estimates based on income level (*Below-Median Income*). Column 2 reports the estimates based on consumer ever incurring an overdraft (*Overdrafter*). Column 3 reports the estimates based on bring hand-to-mount investor (*Hand-to-Mouth*). Column 4 reports the estimates based on investors' 12-month normalized salary volatility (*Salary Volatility*). The estimates of the intercept and fixed effects are omitted for brevity. 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.

Panel A: Crypto Investment

	Log Crypto Investment ($)			
	(1)	(2)	(3)	(4)
Investor CPI	1.817***	1.795***	1.776***	1.664***
	(24.31)	(25.97)	(26.48)	(20.50)
Investor CPI × Below-Median Income (1/0)	-0.1372**			
	(-2.215)			
Investor CPI × Overdrafter (1/0)		-0.1368**		
		(-2.280)		
Investor CPI × Hand-to-Mouth (1/0)			-0.2613***	
			(-2.712)	
Salary Volatility				-0.0161*
				(-1.855)
Investor CPI × Salary Volatility				0.3237***
				(3.975)
N	3,115,598	3,115,598	3,115,598	2,682,668
R-squared	0.35	0.35	0.35	0.36
Person FEs	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

Panel B: Traditional Investment

	Log Traditional Investment ($)			
	(1)	(2)	(5)	(4)
Investor CPI	2.671***	2.565***	2.446***	2.492***
	(32.40)	(34.08)	(33.59)	(27.99)
Investor CPI × Below-Median Income (1/0)	-0.6518***			
	(-10.42)			
Investor CPI × Overdrafter (1/0)		-0.6371***		
		(-10.68)		
Investor CPI × Hand-to-Mouth (1/0)			-0.9563***	
			(-12.13)	
Salary Volatility				-0.0006
				(-0.0639)
Investor CPI × Salary Volatility				0.1441*
				(1.676)
N	3,115,598	3,115,598	3,115,598	2,682,668
R-squared	0.59	0.59	0.59	0.59
Person FEs	Yes	Yes	Yes	Yes
State × Income Class × Month FEs	Yes	Yes	Yes	Yes

Table IA.X. Definitions of Variables

Variable	**Definition**
Retail Investments and Returns	
Log Crypto Investment ($)	The natural logarithm of the one plus the sum of all debits where merchant name or transaction description contains the name of a crypto trading venue (e.g., crypto exchange) in a given period (month or week, as appropriate)
Crypto Investment Likelihood (1/0)	Dummy for making a crypto deposit in a given period (month or week, as appropriate)
Log Traditional Investment ($)	The natural logarithm of the one plus the sum of all debits where the transaction category is "Securities trades" (e.g., investments through traditional brokerages such as Fidelity, Charles Schwabb) or where merchant name or transaction description contains the name of a FinTech brokerage (e.g., Robinhood, Acorns) 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)
Log Traditional Non-FinTech Investment ($)	The natural logarithm of the one plus the sum of all debits where the transaction category is "Securities trades," except where merchant name or transaction description contains the name of a FinTech brokerage, in a given period (month or week, as appropriate)
BTC Return (%)	Bitcoin return, represented by the percent change of Bitcoin price from the previous year to this year.
BTC Price ($)	Bitcoin price in U.S. dollars
BTC Volume (#)	Bitcoin trading volume
S&P 500 Return (%)	Return on S&P 500 Index
Income and Consumption	
% 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)
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
Total Spending ($)	Sum of all spending transactions in a given month
Credit Card Spending ($)	Sum of all credit card transactions in a given month
Income Class ($)	Dummy for one of seven income classes, as defined by data provider: $0–$25k, $25k–$45k, $45k–$60k, $60k–$75k, $75k–$100k, $100k–$150k, $150k+)

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
Covid Adopter (1/0)	Dummy that equals to 1 for consumers who invested in crypto for the first time from January 2020 to December 2020 and 0 otherwise
High Inflation Adopter (1/0)	Dummy that equals to 1 for consumers who invested in crypto for the first time from January 2021 to the end of the sample (i.e., June 2023) and 0 otherwise
Below-Median Income (1/0)	Dummy for investors' income being below the sample median income
Overdrafter (1/0)	Dummy that equals 1 if an investor has ever incurred in overdraft fee and 0 otherwise
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
Income Shocks, Stimulus Payments, and Inflation Exposure	
Positive Income Shock	Weeks where the individual's salary is *more* than 0.5 times the rolling 12-month salary standard deviation above the rolling 12-month salary average
Negative Income Shock	Weeks where the individual's salary is *less* than the rolling 12-month salary average subtracted by 0.5 times the rolling 12-month salary standard deviation
Stimulus I, II, III	Stimulus check payments by round
Investor CPI	Measure of inflation exposure at the consumer-month level constructed based on the annualized monthly change 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 preceding 12 months, measured in decimal points
Inflationary Period	Dummy for time period from January 2021 to the end of the sample (i.e., June 2023)
Chg Consumer Sentiment	Monthly change in the University of Michigan Consumer Sentiment Index, measured in decimal points
Chg Consumer Confidence	Monthly change in the Conference Board Consumer Confidence Index, measured in decimal points