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

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ABSTRACT

We provide a first look into the drivers of household cryptocurrency investing. Analyzing consumer transaction data for millions of U.S. households, we find that, except for high-income early adopters, cryptocurrency investors resemble the general population. These investors span all income levels, with most dollars coming from high-income individuals, similar to equity investors. High past crypto returns and personal income shocks lead to increased cryptocurrency investments. Higher household-level inflation expectations also correlate with greater crypto investments, aligning with hedging motives. For most U.S. households, cryptocurrencies are treated 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 regarding this growth is that it represents an increase in exposure to risks most households may not fully understand. This issue is exacerbated by the ambiguity surrounding the current investor demographic—whether they are affluent individuals diversifying their assets, or lower-income households allocating scarce resources in pursuit of a windfall akin to a lottery jackpot. The inherent anonymity of public blockchains has left room only for conjecture regarding the identities and motives propelling the swift uptick in retail investment in the crypto sector. For instance, a prevailing hypothesis posits that this upswing in crypto wealth stems from a retail "investment frenzy" and a pervasive "fear of missing out," as individuals scramble to partake in the crypto gold rush.[2] Conversely, another widely held theory suggests that the fixed supply nature of cryptocurrencies presents a viable shield against inflation.[3] However, empirical examination of these questions remains elusive, chiefly hindered by data constraints.

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] 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 wallet address nor into consumers

[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/e.

[2] https://www.nyt.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 vast increases in crypto wealth have filtered through to the general economy, impacting consumers and overall economic activity, see Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter (2023).

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

who have never invested in cryptocurrencies. Second, the data give us a more comprehensive view of investors' finances including 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 other key transactions, including whether consumers 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.

Our exploration unfolds in three phases. Initially, we delve into the attributes of crypto investors, tracing the evolution of their demographic composition and comparing their investment tendencies in cryptocurrencies to those in traditional asset classes. This examination sheds light on whether inherent traits, like risk propensities, significantly dictate their investment conduct. Subsequently, we scrutinize investor reactions to liquidity shocks, quantifying the marginal propensity to invest with respect to incremental disposable income, and how it differs across asset classes. In the final phase, we evaluate the extent to which escalating inflation has fueled investors' attraction towards cryptocurrency investments.

We begin our analysis by documenting several key facts about retail cryptocurrency investing. There is substantial overlap in cryptocurrency and traditional investors, with 80% of crypto investors also investing money in traditional after-tax brokerages and only 9% of all users without traditional investments holding crypto. We also observe a tight correlation between crypto investments and Bitcoin returns 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 demographic information, we provide insights into the characteristics of cryptocurrency investors. First, we seek to understand how the financial characteristics of new crypto investors have evolved over time. We find that early adopters of crypto have relatively higher income and spending and are more likely to be financially sophisticated. Second, we find that—relative to households that do not invest in crypto—crypto investors have somewhat higher incomes, are less financially constrained and significantly more likely to be gamblers. 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.

We next test whether increases in liquidity affect households' propensity to invest in risky asset classes like crypto. We pinpoint instances where individuals receive bonuses larger than the norm, or undergo job transitions or losses, enabling us to discern both temporary and permanent shifts in disposable income. Crypto investment responds significantly to these shocks, with stronger but shorter-lived effects to temporary shocks relative to permanent shocks. However, we find similar patterns, with even larger magnitudes, of traditional investment response to these income shocks.

We then utilize the sizable stimulus checks disbursed during the Covid-19 pandemic as natural experiments to examine investment responses to exogenous income shocks. Using an event-study framework, 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 for both crypto as well as traditional investments. While the qualitative response of crypto and traditional investments to these exogenous income shocks is similar to other income shocks, the magnitudes of the response are much higher. 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 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 consumers' crypto investments adjust in relation to their own experiences with inflation. 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.

Comparing households with similar incomes who reside in the same area but have different exposure to local inflation, we find that households with higher inflation exposure increase their investment in cryptocurrency in both amounts and frequency. 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, and the returns to hedging, are 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 this high-inflation period. We find that traditional investments for both crypto and non-crypto investors respond similarly to consumers' inflation expectations.

Overall, our investigation unveils that unlike equity investments, crypto investments exhibit a pronounced sensitivity to market returns. However, the demographic profile of crypto investors

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

largely mirrors the broader investing population, with most crypto investors also being active equity investors. Households navigate unexpected income shocks by channeling funds into both cryptocurrencies and traditional assets. Finally, our results align with the prevailing notion that cryptocurrencies are perceived as a viable hedge against inflation, with households ramping up their crypto investments amidst heightened inflationary exposure.

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 from an asset pricing perspective. 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 fiscal measures aimed at increasing household liquidity were behind the crypto run-up in 2020–2021. 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.[7]

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

[7] 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.

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 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 manageable 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.[8]

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. For most transactions, we are also able to directly observe the full transaction description which also allows for identification of transactions that involve an exchange.

We exploit this information in the data to identify all account transactions involving crypto

[8] 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. See Baker and Kueng (2022) for a further discussion of this class of household financial transaction data.

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 into their bank account. To compare cryptocurrency investing with traditional investing, we complement these data by creating similar measures of buying and selling traditional assets. 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 from household bank accounts (we cannot observe deposits withheld from paychecks).

Using our transaction data set, we also 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 correlated with sophistication due to one's background and work experience.

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 (Column 1). 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. 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.

C. *Income Shocks*

We use the information from transaction descriptions for deposits (i.e., credits) to identify instances in which individuals experience abnormal income shocks. Income shocks are defined as weeks where the individual's salary differs by more than a standard deviation from 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:

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

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 a standard deviation from the average weekly salary in the next 6 months and the future 6 month average is above the past 12 month average ($|s_{i,t} - \mu_{i,t+1,t+26}| < \sigma_{i,t+1,t+26}$ and $\mu_{i,t-51,t} < \mu_{i,t+1,t+26}$). 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 as well as instances where they move to a higher paying job. The shocks we identify are frequent and sizable. In our sample, the average permanent positive income shock was 69% of weekly income and almost 130% of weekly income for temporary positive income shocks. For negative income shocks, the average shock size was -52% for permanent shocks and -69% for temporary shocks.

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 can be picked up from the transaction descriptions. We identify stimulus payments for

Stimulus I from the size of of tax refunds 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.[9]

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).[10] 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

[9] 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.

[10] 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`.

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

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

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.

Our measure of inflation expectations has a positive correlation of 0.360 with a measure of median expected price change over the following 12 months based on consumer surveys.[12] The mean for the sample of crypto investors is 2.52 percentage points (pp) and the median is 2.09 pp.

The 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

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

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

at the same time but have differential exposure to inflation due to differences in their consumption baskets. We also construct this measure for 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 crypto investors and 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 first-time investors. 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 note a similar 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 in 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. The figure clearly shows that early adopters 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 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 in our sample 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 4% of total income and 5.5% 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 per capita was highest in the Rocky Mountain states, Vermont, and Oregon. By the 2017 Bitcoin price boom, new users had spread to the coasts and were more concentrated in California and New York. 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 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.[13] 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 accounting for approximately 73% of the transactions. However, individuals earning less than $45k still contribute about 11% 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. 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.

We summarize the characteristics of crypto investors in Table I. Columns 3–5 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. Crypto investors have higher incomes, are more likely to gamble, are more financially sophisticated, and tend to invest more in traditional markets than non-crypto investors (Column 2 vs. 6). Comparing 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.

We find similar patterns in cross-sectional regression analysis where we are control for state by income class fixed effects (Table II). Being financially sophisticated increases the probability of be-

[13] 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.

coming a crypto investor by 7.1 pp and being a gambler increases this probability by 8.4 pp. Crypto investors are also less likely to be below-median-income investors, hand-to-mouth consumers, or overdrafters both unconditionally (see Table I Panel A) and after controlling for income (see Table II Panel A).[14]

Our transaction data does not contain individual demographic information such as race or education. However we can infer the zip code of the household's home residence based on location information contained in their transactions. In Panels A and B of Table III, we show the zip code distribution of race and education, respectively, for crypto and non-crypto adopters. On average, late (Covid and high inflation) 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 III, we show that early adopter zip codes are wealthier, with median annual household income about $4,000 higher than late adopters and non-adopters. We report additional zip-level measures related to occupation and industry in Appendix Table IA.I. Overall, zip codes of crypto investors look similar to those of non-investors along most dimensions, with early crypto adopters being somewhat different from 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. However, 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.

[14]We also find some meaningful differences between pre- and post-Covid crypto adopters after conditioning on income and location (Table II Panel B). Pre-Covid crypto adopters are 7.5 pp more likely than post-Covid adopters to be financially sophisticated but 1.1 pp *less* likely to be gamblers.

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 deposits into brokerage accounts (i.e., not investments withheld from paychecks), so we are only capturing active contributions and trading by investors rather than automatic pre-tax contributions.[15]

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, investments in exchanges and in post-tax brokerage accounts are quite comparable. These investments tend to be small, less than \$1,000, but the crypto amounts track the traditional ones closely.

More significant divergences occur for the wealthier individuals, for whom crypto investment tends to be a much 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 than in cryptocurrencies. Thus, lower-income households spend a much higher fraction of their investment money (and salaries) on crypto investment. Lastly, we provide evidence that cryptocurrency does not substantially crowd out other investments in Figure 6 Panel B. Here, 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, proxied by 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. We estimate the following

[15] 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).

monthly 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 percent 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 IV Panel A. We observe a significant and positive relation between both 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. We find that a 1 pp increase in monthly BTC return is associated with a 0.98 pp increase in crypto investing and 1.86 pp increase in crypto withdrawals. 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 IV 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 a rolling 12-month 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).

Table V reports the results for responses in cryptocurrency and traditional investments and withdrawals to positive (Panel A) and negative (Panel B) income shocks. 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 specification is:

$$\begin{aligned} y_{it} = &\alpha_{it} + \beta_{it}\, \mathit{Window\ Around\ Shock}_{it} \times \mathit{After\ Shock\ Weeks}_{it} \\ &+ \gamma_{it} \mathit{After\ Shock\ Weeks}_{it} + \delta_{it}\, \mathit{Window\ Around\ Shock}_{it} + \varepsilon_{it}, \end{aligned} \tag{4}$$

where y_{it} represents the log dollar amount of investment in crypto or traditional asset classes. $\mathit{Window\ Around\ Shock}_{it} = 1$ for the $+/-6$ week window around the income shocks and is equal to 0 for a random $+/-6$ week period in the past for a given retail investor. $\mathit{After\ Shock\ Weeks}_{it}$ summarizes the weeks around the window into a single indicator where 1 represents weeks 0 to 1 after the shock. To capture differences across individuals, we include person fixed effects as well as week by state by income class fixed effects to 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 exposure. This is true for both permanent and temporary shocks, but the economic magnitudes of the effects are larger for temporary positive shocks.

Specifically, crypto (traditional) investment increases by 0.39% (1.49%), on average, in the first two weeks of permanent income shocks, while the increase in the first two weeks of temporary income shocks is 0.94% (3.89%), respectively. In contrast, Panel B shows that investors withdraw from both markets in response to negative income shocks, but only in response to temporary shocks. The economic magnitudes of the effects are also smaller. On average, crypto (traditional) withdrawal increases by 0.16% (0.14%) in the first two weeks of temporary negative shocks. The results are robust to estimating a linear probability model where the dependent variable is the monthly investment likelihood (Appendix Table IA.II).

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_k's separately for each type of shock:

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

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.

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 the city of residence. 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 (5). 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 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 practically disappears when we restrict the sample to users who do not have frequent traditional deposits (Appendix Figure IA.I). As shown in Table V, 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 largely similar for crypto investors and non-crypto investors (Appendix Figure IA.II).

We also find evidence of heterogeneity in investment response to positive income shocks that are temporary in nature by several investor characteristics. Financially sophisticated individuals do not increase their crypto investments after temporary positive shocks more than non-sophisticated investors do. However, they do increase their traditional investments by 7.39% more than non-sophisticated investors do after these shocks. Below-median-income investors increase their crypto investments slightly (0.32%) more than above-median-income investors after such shocks, but the result reverses for traditional investments (Appendix Tables IA.IV and IA.V).

Overall, it seems that there is a significant response of crypto investment to increases in disposable income, especially for liquidity-constrained individuals. While we observe these income shocks across the entire sample period, at least some of these changes in income may be anticipated. The next section exploits another source of income shocks, the stimulus payments during the Covid-19 crisis, to estimate investors' marginal propensity to invest. 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 investments in 2020, which we document earlier, coincided with portions of the 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.[16] 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.

We use the staggered timing of the arrival of stimulus payments in retail investors' bank accounts as a source of quasi-exogenous variation in liquidity available for investing. Table VI 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 V.[17] 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 VI 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. Specifically, crypto investment increases by 1.35% in the first two weeks after Stimulus I and by 4.95% after Stimulus III. The coefficient for Stimulus II is also positive and similar in size, but not statistically significant. If we re-define the after-shock indicator to only include the

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

[17] The *Window Around Shock*$_{it}$ indicator is omitted due to collinearity.

week of Stimulus II payment, the coefficient becomes significant. These results corroborate 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, though smaller than, indirect evidence in Divakaruni and Zimmerman (2023), suggesting that a large portion of stimulus money possibly went to consumption.

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. Table VI Panel B reports the effects of stimulus payments on traditional investments. Like crypto investments, traditional investments increase in the two weeks surrounding stimulus payments for Stimulus I and III. The coefficients and economic magnitudes are about twice the size of those for crypto investments. Specifically, traditional investment increases by 4.0% in the first two weeks after Stimulus I and by 7.4% after Stimulus III. The negative coefficient for Stimulus II appears at odds with these results and indicates a decrease in traditional investments by around 2.3%. 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.

To more clearly examine the pattern of crypto and traditional investments after the stimulus, we use 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:

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

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.[18] As

[18] 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

with other income shocks, we include investor and state of residence by income class by week fixed effects α_{it} and cluster standard errors at the investor level.

We plot the coefficients of interest β_k from Equation (6) estimated for Stimulus I, along with 95% confidence intervals, in Figure 8. Consistent with regression evidence, we observe a statistically significant spike in crypto investment in the week of stimulus payment that subsides in the six weeks after the payment date, similar 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, finding results that are similar but more short-lived. 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).

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 cryptocurrency investing. We also examine heterogeneity in crypto and traditional investing responses to inflation along dimensions like investor sophistication, experience, and financial 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.[19] 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.[20]

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 the money illusion. It is unclear which of these theoretical frameworks, if any, are applicable to investments in cryptocurrencies.

On the one hand, cryptocurrencies as financial assets do not have cash flows or dividends

[19]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`.

[20]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.

which can grow with inflation and provide a direct hedge against consumer 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 volatile assets such as cryptocurrencies and 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.[21] 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

[21] 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.

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. Empirically, individual-level inflation exposure allows us to conduct within-investor tests, controlling for time trends and time-varying local economic factors.

We report the baseline results for our sample of crypto users in Table VII. 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 much more pronounced during periods of high inflation (Column 2). A one standard deviation increase in the annualized investor-level CPI inflation is associated with an increase in crypto investment by an economically significant average of 3.13% across the entire sample and 6.60% for the inflationary period.[22]

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 find directionally similar effects for the response of traditional investments to our measure of investor-level inflation in Columns 3 and 4 of Table VII. 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 eco-

[22]Computations: $\exp(0.8608 \times 3.58/100) - 1 = 0.0313$ and $\exp((0.2438 + 1.541) \times 3.58/100) - 1 = 0.0660$.

nomic magnitudes of the effects are, however, somewhat larger for traditional investments. A one standard deviation increase in the investor-level CPI inflation is associated with an increase in traditional investment by 5.56% across the entire sample and 13.88% for the inflationary period. These results persist even when we exclude investments through FinTech brokerages (e.g., Robinhood, Acorns) from the definition of traditional investing because many FinTech brokerages launched crypto investing options in the last few years of our sample period (Appendix Table IA.VIII).[23]

In supplementary analysis, we compare the response of traditional investments by crypto investors to those by non-crypto investors. We find generally similar effects with coefficients that are about two times smaller for non-investors (Appendix Table IA.IX). 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 relative effects in percentage terms are comparable across the two sets of investors.[24]

C. Heterogeneous Response of Crypto Investment to Inflation

Finally, we examine differential responses of crypto investing to inflation based on several measures of financial sophistication, risk attitudes, and crypto investing experience. Panel A of Table VIII reports the results where we interact 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 VIII indicate that sophisticated investors are approximately twice as responsive to inflation expectations as non-sophisticated investors. Column 2 of Table VIII reports positive coefficients for an interaction with gamblers, suggesting that gamblers may be more comfortable investing in high-risk assets such as

[23]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.

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

crypto during periods of economic uncertainty or may pursue hedging strategies more aggressively.

We now turn to three measures of retail investors' experience with the crypto market. In Table VIII Column 3 we find that early adopters of crypto invest less in crypto when their inflation exposure increases.[25] In contrast, we find that those who invested for the first time during COVID or later are 3 to 4.5 times more responsive to an increase in inflation exposure.

Panel B of Table VIII 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 VIII, 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.XI).

In Table IX, Columns 1–3 we demonstrate that the elasticity of crypto investments with respect to inflation expectations does not seem to depend on consumers' constraints. However, we document in Column 4 that higher variability in salary income is positively related to crypto investing when inflation exposure is high. In Panel B of Table IX, we note variation in the response of traditional investments to inflation exposure across these same budget constraint interactions. 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. Overall, our findings suggest that investors likely do consider cryptocurrencies as an inflation hedge, at par with traditional securities.

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

V. Conclusion

This paper provides the first comprehensive description of crypto investors and their motivations for investing in crypto. Rather than using data from public blockchains, which only provide information regarding crypto trades themselves, we use detailed bank account transactions that provide a representative sample of U.S. consumers. The advantages of our data are that they offer both information about deposits to and withdrawals from crypto accounts at centralized exchanges like Coinbase as well as information about crypto investors' (and non-investors') other non-crypto financial transactions. We investigate how investor characteristics, observed returns, liquidity, and inflation expectations drive the propensity to invest in crypto as well as traditional asset classes.

We start by examining the characteristics of crypto investors and the evolution of retail crypto investing. We document significant retail investment in crypto during booms in Bitcoin prices in 2017 and 2020–2021. 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 appear 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 cryptocurrency 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 now distributed across the income spectrum and have been significantly more geographically widespread across the country.

We next examine several potential drivers of crypto investing. First, we note that liquidity shocks, in the form of significant changes in income or exogenous stimulus check payments, drive spikes in crypto investing. While we find that investors did invest a portion of their additional disposable income into crypto, these amounts entailed only a small fraction of overall crypto investment in recent years. In addition, investors' behavior in response to such shocks is even larger for traditional investments.

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 categorical inflation and 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 incomes, providing some evidence that crypto may be seen as one potential hedge against rising inflation.

Our results suggest 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.

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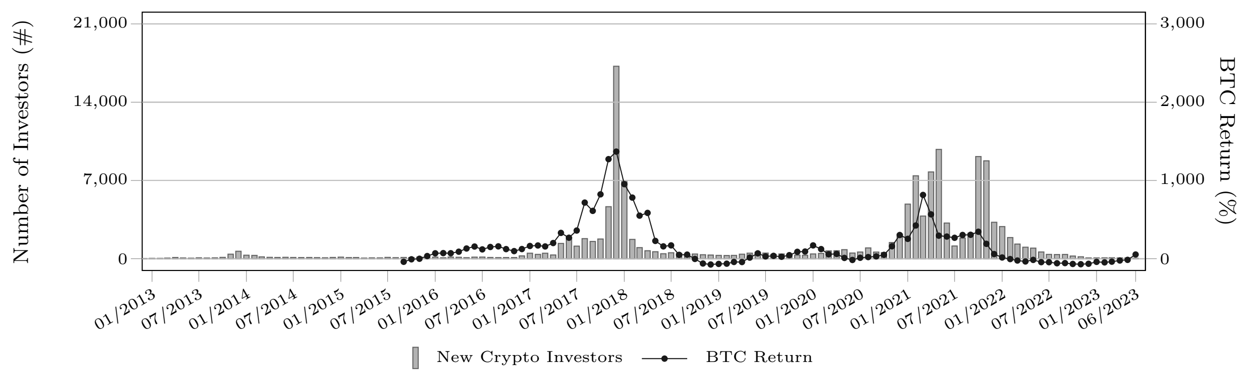
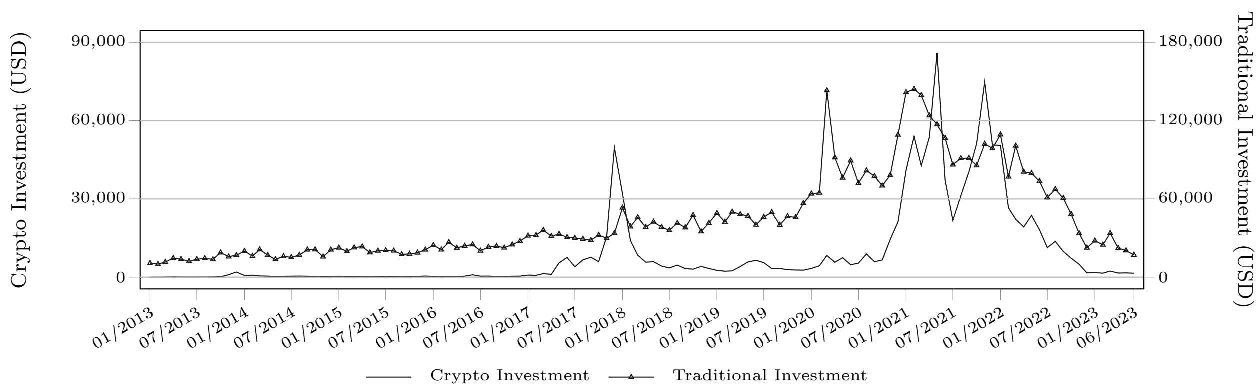
Figure 1. Crypto and Traditional Investment Dynamics

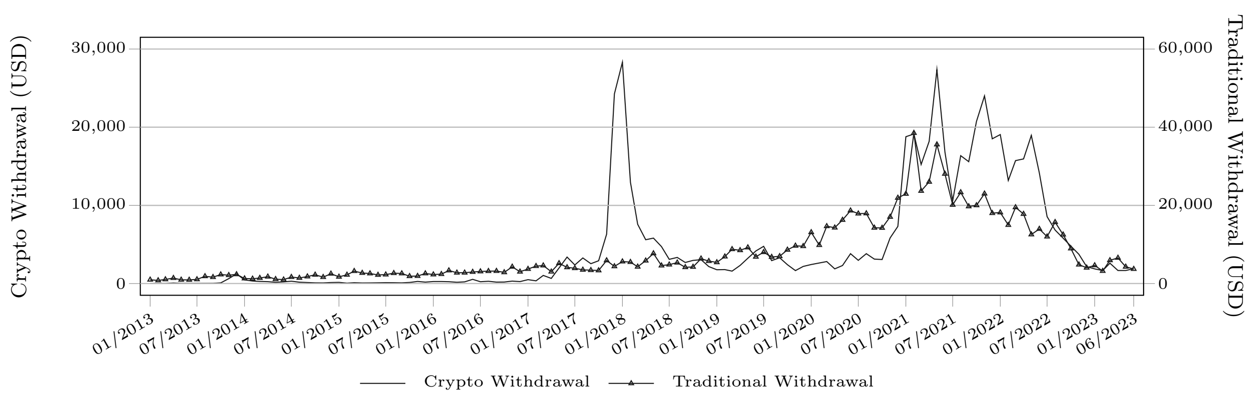
Panel A: Monthly New Crypto Investors (#) and BTC Return (%)



Panel B: Monthly Cryptocurrency and Traditional Investments ($)

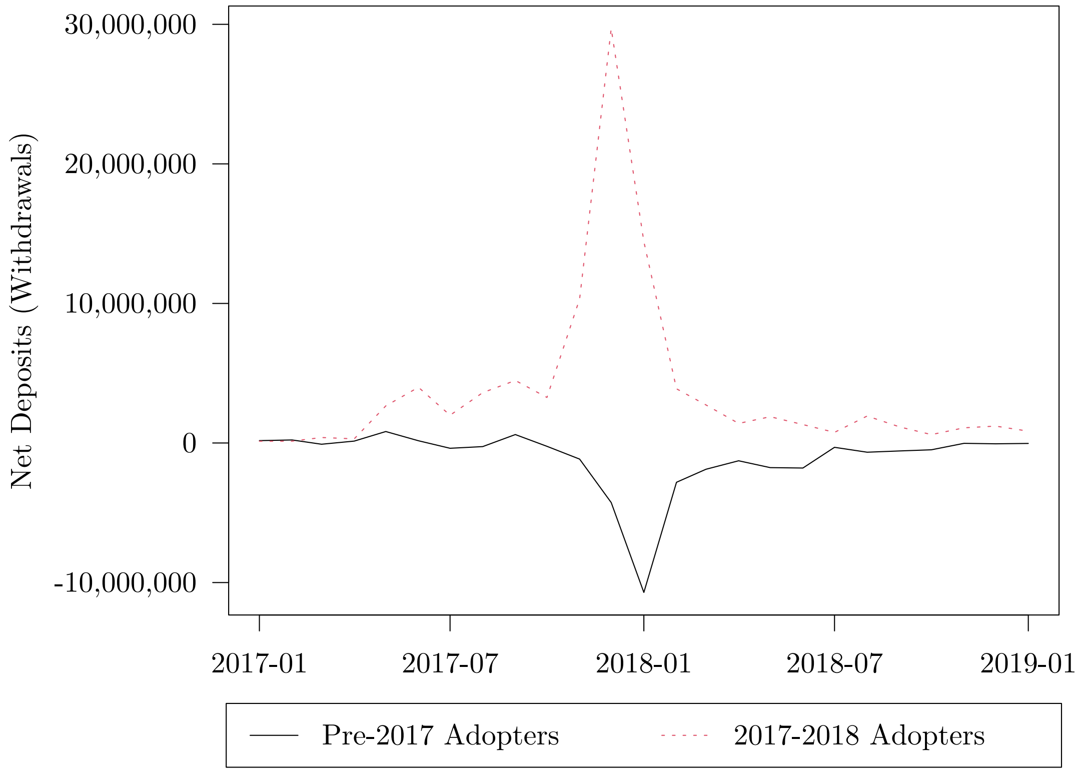


Panel C: Monthly Cryptocurrency and Traditional Withdrawals ($)



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. 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.

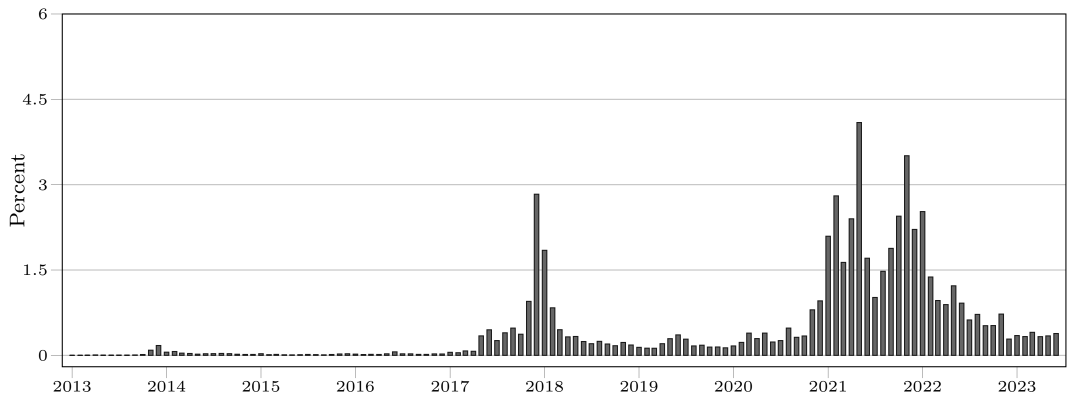
Figure 2. Net Deposits (Withdrawals) by Crypto Adoption Cohort



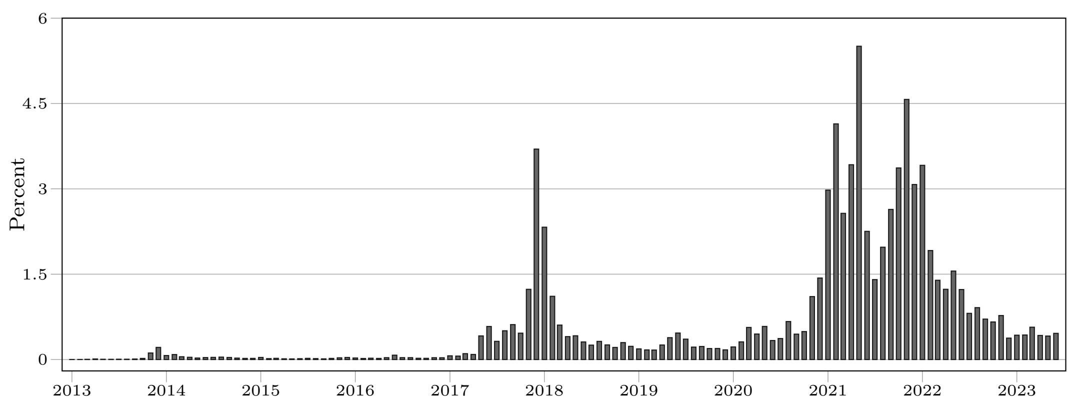
This figure plots net deposits to (and net withdrawals from) cryptocurrency exchanges, splitting the sample into those who first interacted with an exchange prior to or after 2017. We note substantial net withdrawals from exchanges by pre-2017 adopters and substantial net deposits from those adopting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

Figure 3. Crypto Investment Share

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

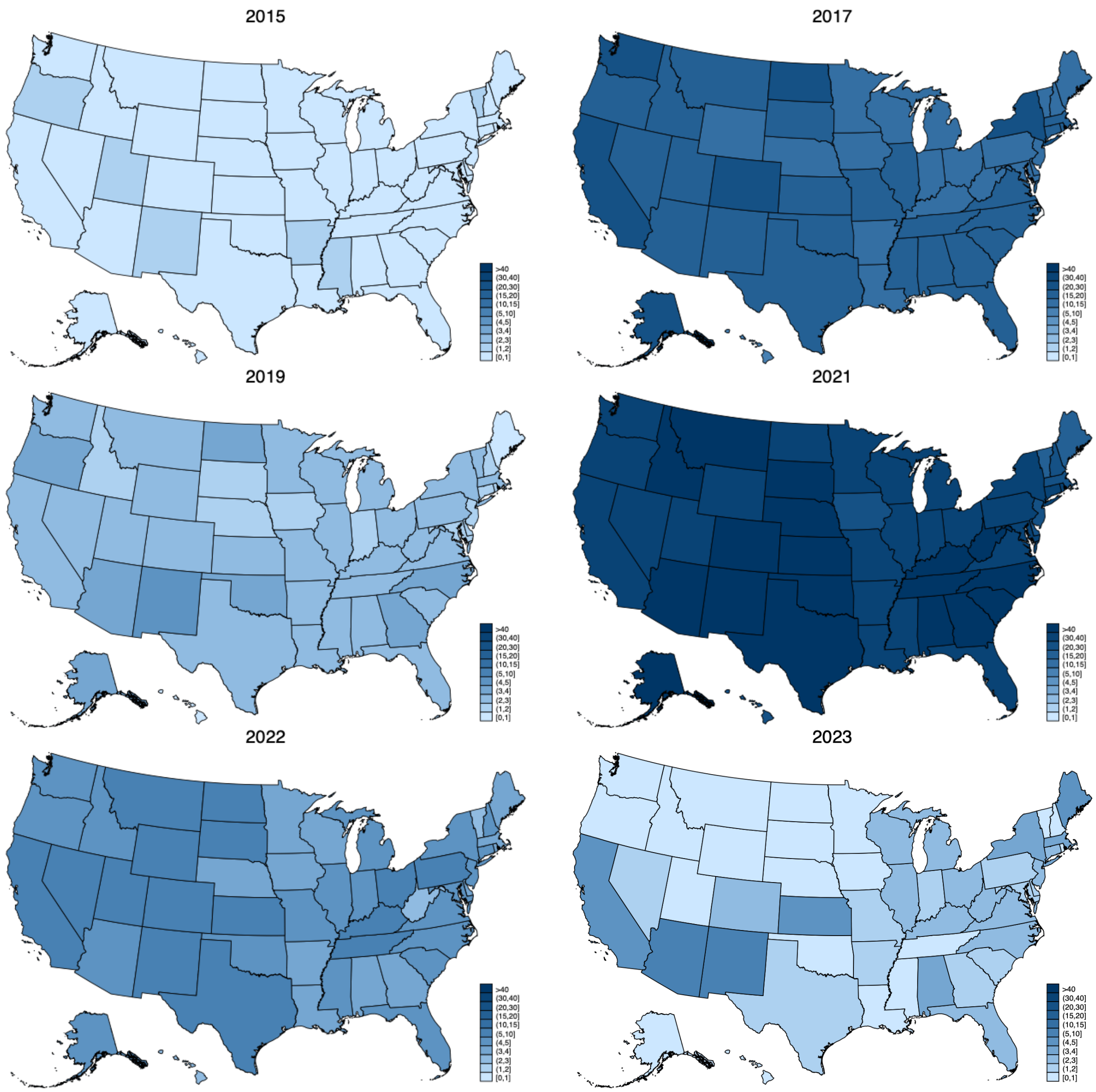


Panel B: Monthly Cryptocurrency Investment as a Percentage of Total Spending



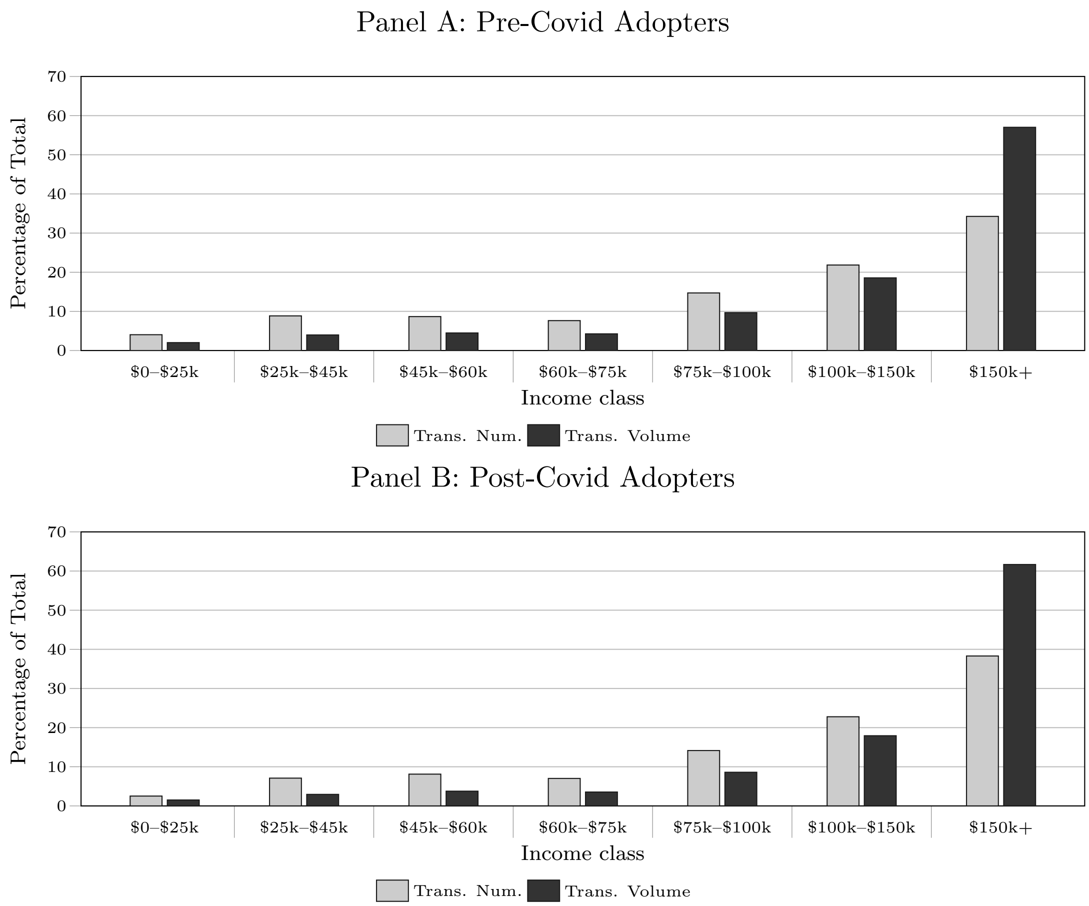
This figure illustrates the share of cryptocurrency retail investment. Panel A plots monthly dollar cryptocurrency investment amount as a percentage of total income. Panel B plots monthly dollar cryptocurrency investment amount as a percentage of total spending.

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.

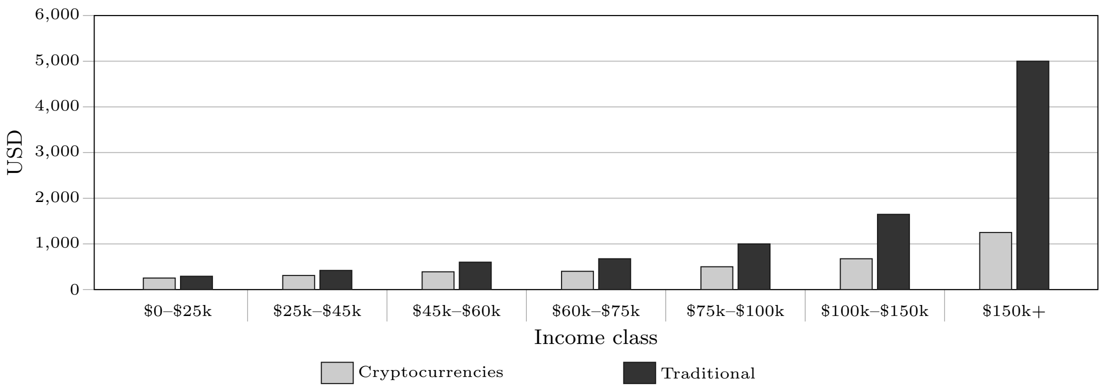
Figure 5. Percentage of Investors by Income Class, as of June 2023



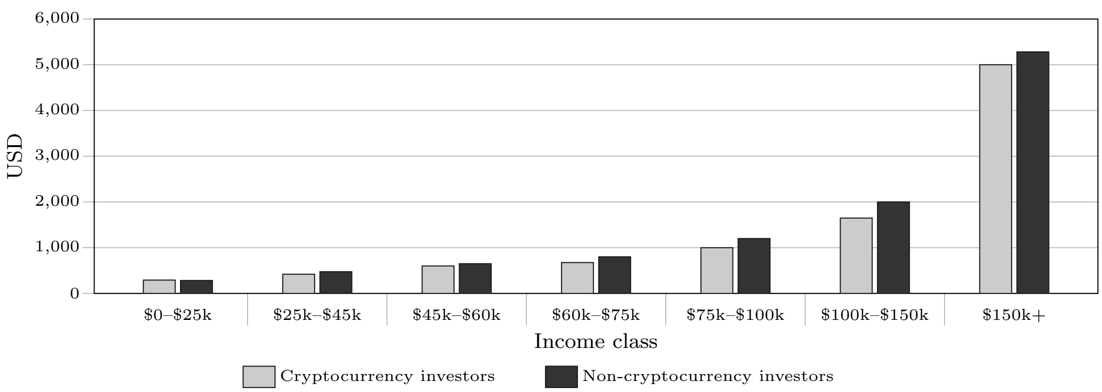
This figure displays the distribution of cryptocurrency investment across income classes by number of transactions and dollar volume. Panel A plots the distribution of cryptocurrency investment by income class for cryptocurrency investors who began investing in crypto prior to Covid (pre-2020). Panel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

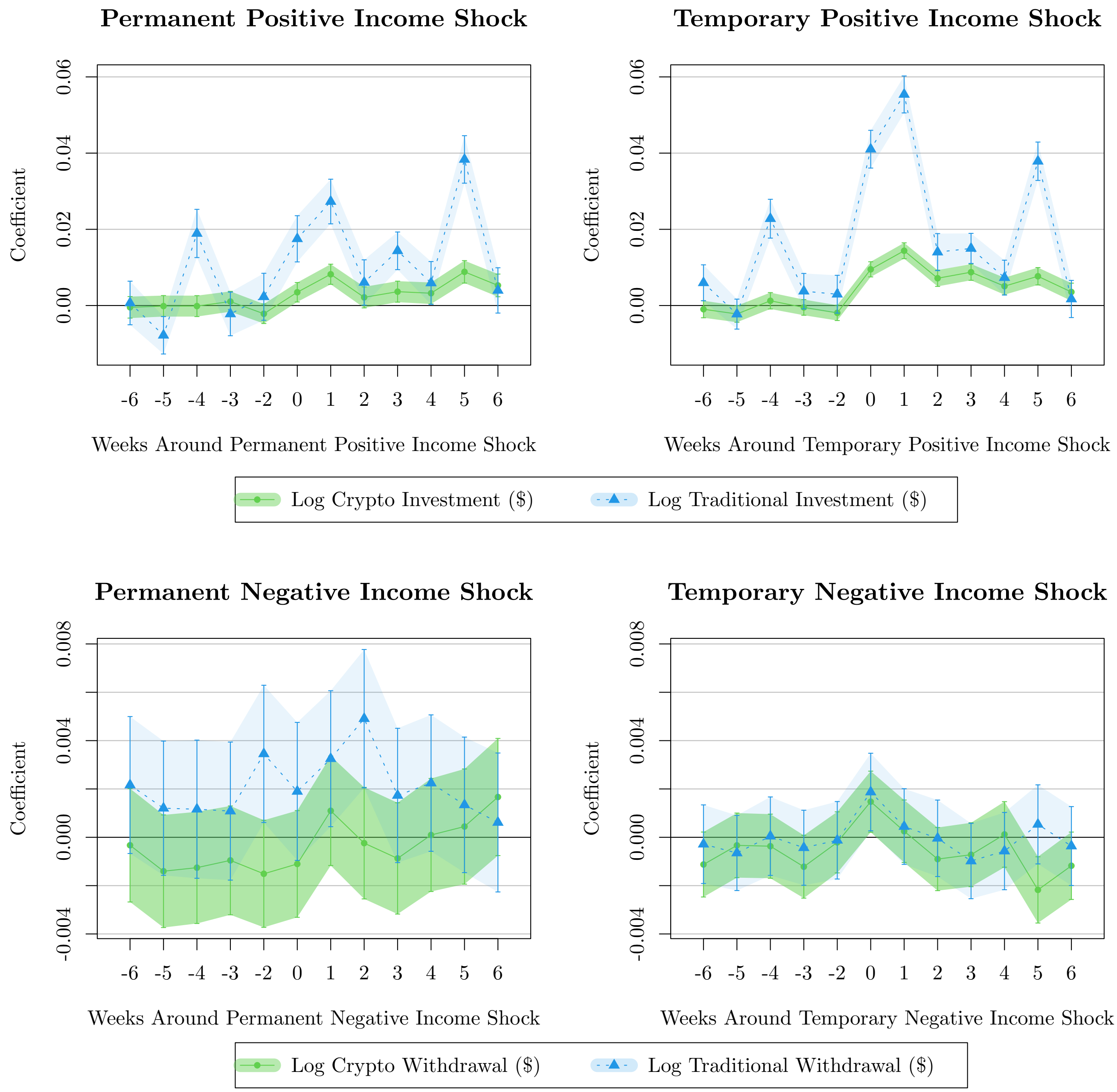


Panel B: Traditional Investment: Crypto v. Non-Crypto Investors



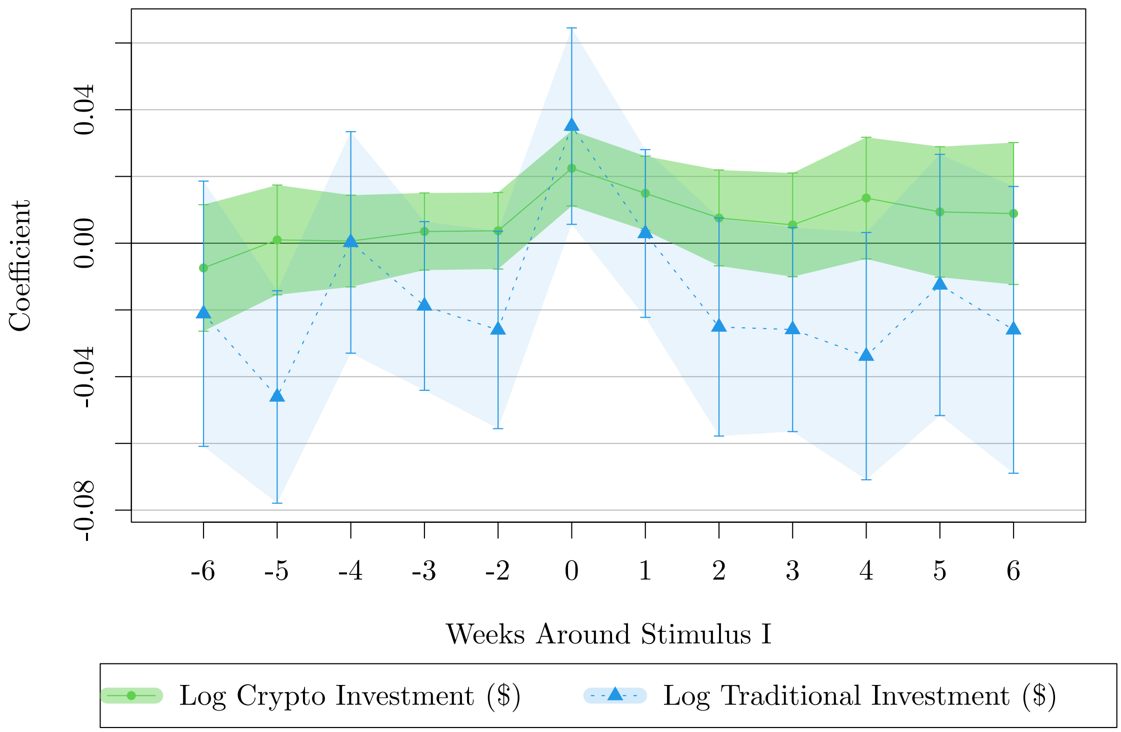
This figure plots median annual investment in crypto and traditional assets by income class. Panel A displays the distribution of traditional investment and cryptocurrency investment across asset and income classes by dollar volume for cryptocurrency investors. Panel B displays the distribution of traditional 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 (5) 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 (6) 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.XIII.

		Full Sample	Crypto Investors	Crypto Adoption Cohort			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. Probability of Being a Crypto Investor by Investor Characteristics

This table reports OLS estimates of an investor's probability of being a crypto investor and a Pre-Covid investor based on investors' risk attitude, experience, and budget constraints. Panel A reports the probability estimates of an investor being a crypto investor. Panel B reports the probability of a crypto investor being a pre-Covid adopter. State $\times$ income class fixed effects are included where state and income class are defined as the most frequent value in the whole sample. The estimates of the intercept and fixed effects are omitted for brevity. Standard errors are clustered at state $\times$ income class level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. t-statistics are presented in parentheses.

Panel A: Crypto Investor

	Crypto Investor (1/0)				
	(1)	(2)	(3)	(4)	(5)
Sophisticated (1/0)	0.0711***				
	(26.66)				
Gambler (1/0)		0.0835***			
		(46.46)			
Below-Median Income (1/0)			-0.0068***		
			(-4.595)		
Hand-to-Mouth (1/0)				-0.0240***	
				(-10.88)	
Overdrafter (1/0)					-0.0013
					(-0.6376)
N	828,551	828,551	828,551	828,551	828,551
R-squared	0.01	0.02	0.01	0.01	0.01
State $\times$ Income Class FE	Yes	Yes	Yes	Yes	Yes

Panel B: Pre-Covid Adopter

	Pre-Covid Adopter (1/0)				
	(1)	(2)	(3)	(4)	(5)
Sophisticated (1/0)	0.0745***				
	(14.59)				
Gambler (1/0)		-0.0114***			
		(-3.108)			
Below-Median Income (1/0)			0.0147***		
			(3.334)		
Hand-to-Mouth (1/0)				-0.0633***	
				(-8.878)	
Overdrafter (1/0)					0.0598***
					(11.15)
N	145,641	145,641	145,641	145,641	145,641
R-squared	0.01	0.01	0.01	0.01	0.02
State $\times$ Income Class FE	Yes	Yes	Yes	Yes	Yes

Table III. 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 Cohort			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 IV. 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 V. 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 (5), 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)	0.0039***	0.0094***	0.0148***	0.0382***
	(4.931)	(15.01)	(10.20)	(30.83)
After Shock Weeks (1/0)	0.0002	0.0010***	0.0054***	0.0040***
	(0.5424)	(2.585)	(4.817)	(4.330)
Window Around Shock (1/0)	0.0024***	0.0027***	0.0060***	0.0064***
	(3.281)	(4.987)	(4.899)	(7.334)
Shock Type	Permanent	Temporary	Permanent	Temporary
N	11,304,105	21,303,667	11,304,105	21,303,667
R-squared	0.15	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)	0.0004	0.0016***	0.0008	0.0014***
	(0.5983)	(4.308)	(0.9770)	(3.312)
After Shock Weeks (1/0)	9.72×10^{-5}	-0.0002	-0.0003	-0.0001
	(0.2757)	(-1.010)	(-0.6148)	(-0.4174)
Window Around Shock (1/0)	0.0003	0.0008***	-0.0002	0.0009***
	(0.7204)	(3.491)	(-0.5005)	(3.601)
Shock Type	Permanent	Temporary	Permanent	Temporary
N	5,388,627	17,043,564	5,388,627	17,043,564
R-squared	0.10	0.05	0.11	0.06
Person FE	Yes	Yes	Yes	Yes
Week × State × Income Class FEs	Yes	Yes	Yes	Yes

Table VI. 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 (6), 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)	0.0134***	0.0128	0.0484***
	(4.006)	(1.504)	(6.385)
After Shock Weeks (1/0)	-0.0002	0.0051	-0.0008
	(-0.0901)	(1.207)	(-0.3421)
N	1,931,987	1,524,356	1,884,997
R-squared	0.23	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)	0.0394***	-0.0228**	0.0716***
	(5.921)	(-1.983)	(7.529)
After Shock Weeks (1/0)	0.0057	0.0019	0.0013
	(1.409)	(0.2448)	(0.2263)
N	1,931,987	1,524,356	1,884,997
R-squared	0.25	0.24	0.25
Person FE	Yes	Yes	Yes
Week × State × Income Class FEs	Yes	Yes	Yes

Table VII. 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 VIII. 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 IX. 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

Internet Appendix to

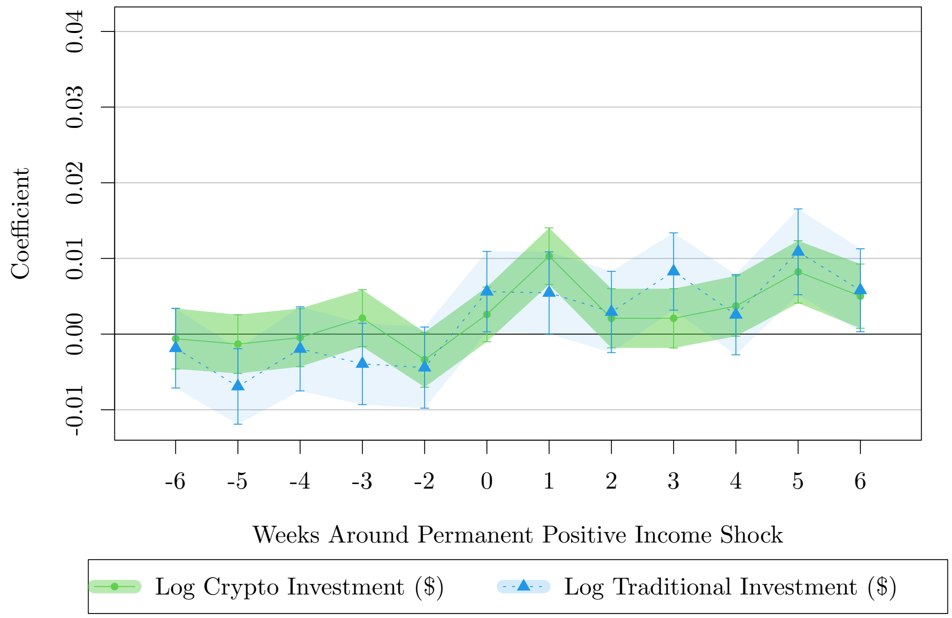
“Who Invests in Crypto?

Wealth, Financial Constraints, and Risk Attitudes”

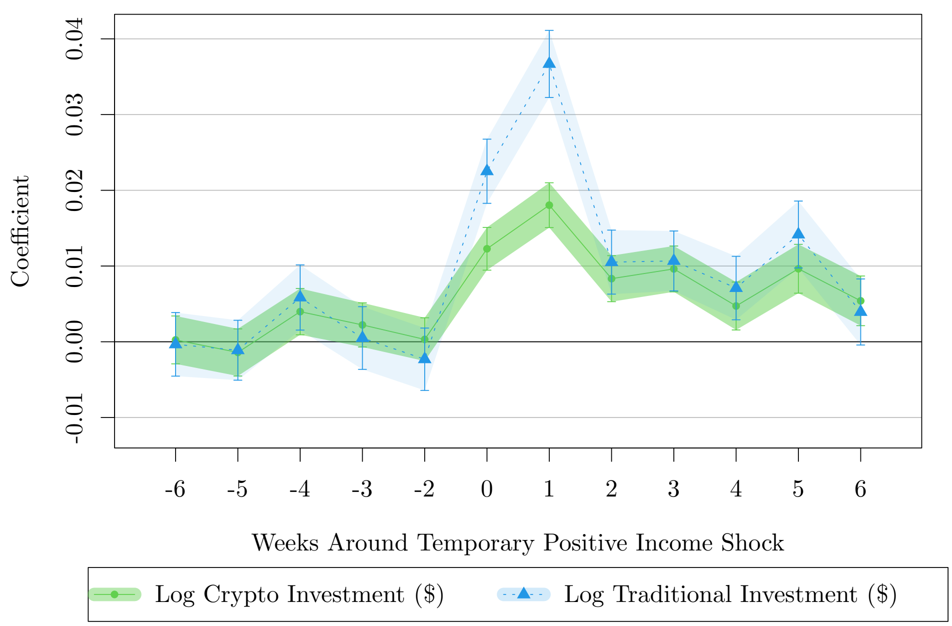
FOR ONLINE PUBLICATION

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



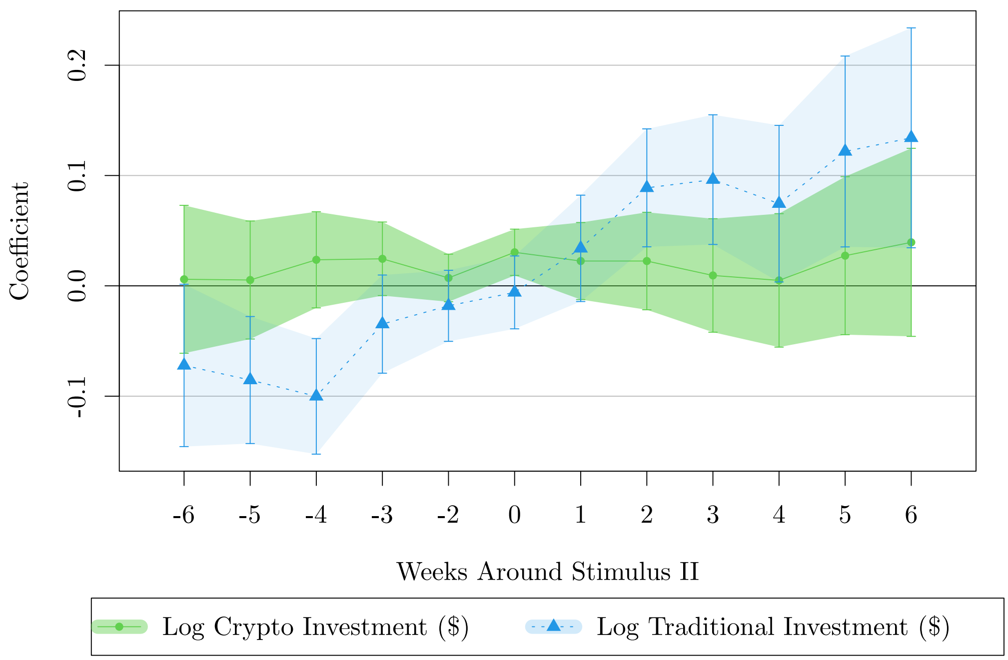
These figures display the difference in cryptocurrency and traditional investment before v. after positive income shocks for users who do not have frequent annual traditional deposits, defined as investors not in the top quartile of the number of deposits per year. All figures plot β_k from Equation (5) 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

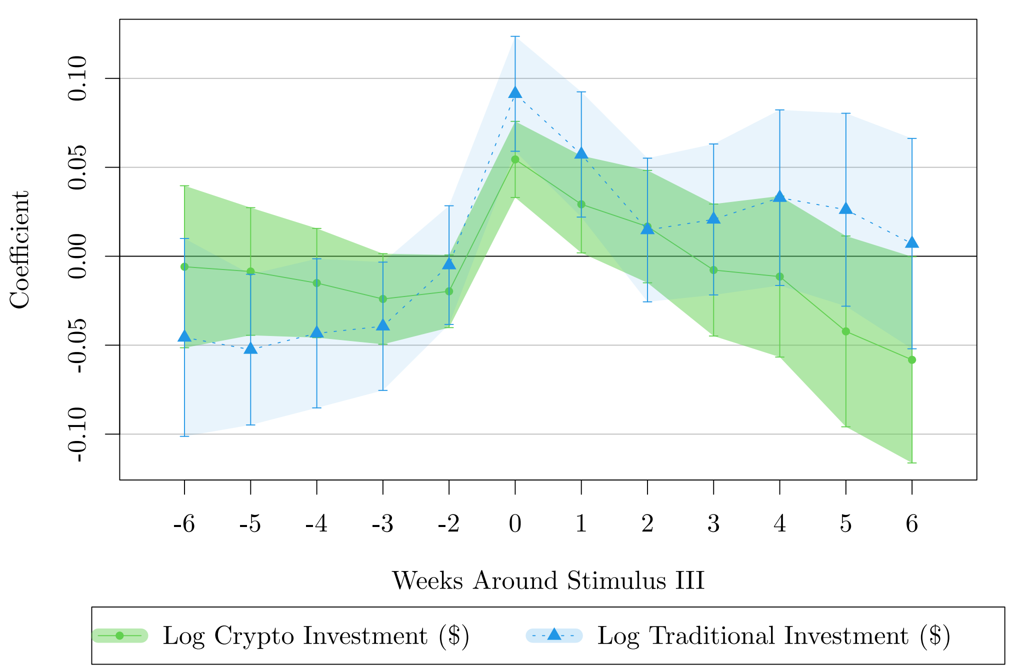
These figures display the difference in traditional investment and withdrawal before v. after a positive and negative income shock for crypto and non-crypto investors. All figures plot β_k from Equation (5) for the log dollar amount invested and withdrawn in the traditional asset class.

Figure IA.III. Retail Investment Responses after Stimulus Checks

Panel A: Retail Investment Responses After Stimulus II



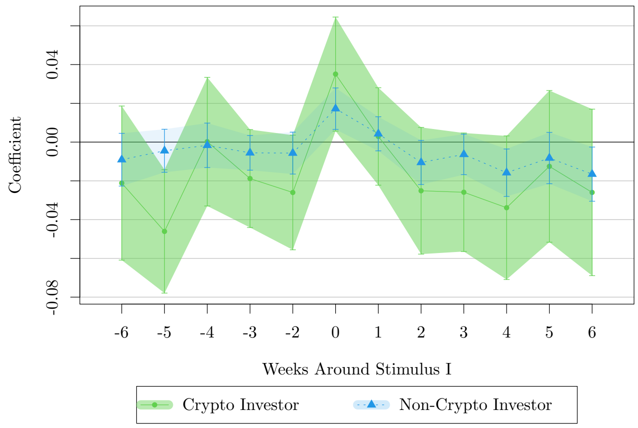
Panel B: Retail Investment Responses After Stimulus III



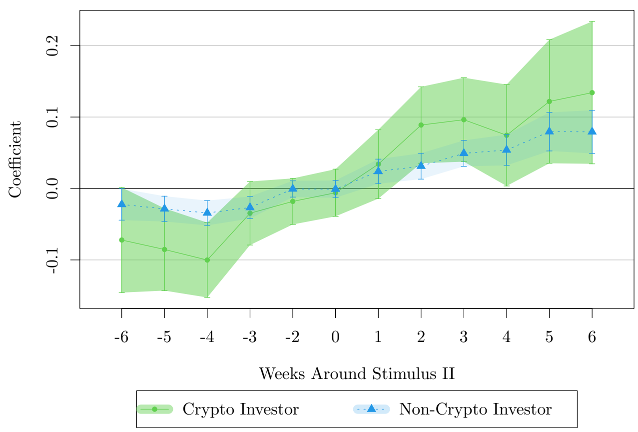
These figures display the difference in cryptocurrency and traditional investment before v. after receiving the second and third stimulus check. The figure plots β_k from Equation (6) for the log dollar amount invested in either asset class.

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

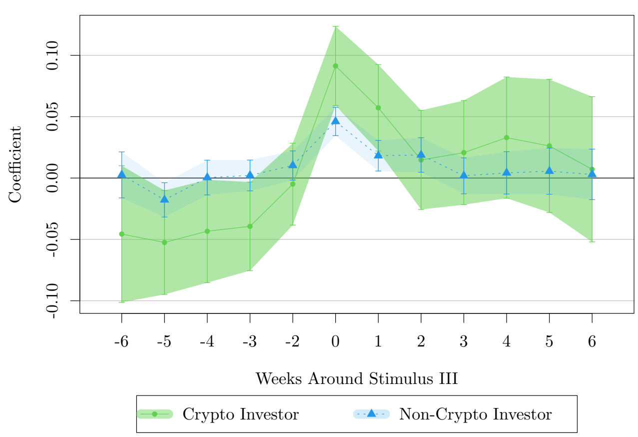
Panel A: Retail Traditional Investment Response After Stimulus I



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 (6) 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 III. 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 in Equation (5), 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***	0.0023***	0.0052***
	(4.132)	(11.61)	(9.022)	(24.67)
After Shock Weeks (1/0)	4.78×10^{-5}	0.0002**	0.0010***	0.0007***
	(0.6046)	(2.380)	(5.144)	(4.104)
Window Around Shock (1/0)	0.0005***	0.0005***	0.0009***	0.0011***
	(3.475)	(4.590)	(4.047)	(6.726)
Shock Type	Permanent	Temporary	Permanent	Temporary
N	11,304,105	21,303,667	11,304,105	21,303,667
R-squared	0.16	0.13	0.20	0.19
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)	0.0001	0.0003***	6.77×10^{-5}	0.0003***
	(1.082)	(4.724)	(0.4939)	(3.848)
After Shock Weeks (1/0)	-3.17×10^{-5}	-4.2×10^{-5}	-2.61×10^{-5}	-5.88×10^{-5}
	(-0.5345)	(-1.138)	(-0.3006)	(-1.138)
Window Around Shock (1/0)	1.71×10^{-5}	0.0001***	-1.71×10^{-5}	0.0002***
	(0.2341)	(2.856)	(-0.1935)	(4.092)
Shock Type	Permanent	Temporary	Permanent	Temporary
N	5,388,627	17,043,564	5,388,627	17,043,564
R-squared	0.10	0.05	0.10	0.06
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 in Equation (5), 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)	0.0148***	0.0377***
	(10.25)	(30.57)
After Shock Weeks (1/0)	0.0052***	0.0041***
	(4.728)	(4.367)
Window Around Shock (1/0)	0.0059***	0.0063***
	(4.932)	(7.307)
Shock Type	Permanent	Temporary
N	11,304,105	21,303,667
R-squared	0.20	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)	0.0006	0.0008**
	(1.060)	(2.374)
After Shock Weeks (1/0)	-0.0004	-7.26×10^{-5}
	(-1.005)	(-0.3151)
Window Around Shock (1/0)	-0.0004	0.0005**
	(-0.9505)	(2.511)
Shock Type	Permanent	Temporary
N	5,388,627	17,043,564
R-squared	0.12	0.07
Person FE	Yes	Yes
Week × State × Income Class FEs	Yes	Yes

Table IA.IV. Heterogeneous Investment Response to Temporary Positive Income Shocks Sophisticated Investors

This table reports the heterogeneous difference in cryptocurrency and traditional investment before v. after a temporary positive income shock for sophisticated investors. The window around shock is the T_{it} variable is equation (5), 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. 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)
After Shock Weeks (1/0) × Window around Shock (1/0) × Sophisticated (1/0)	0.0031	0.0713***
	(1.269)	(12.28)
After Shock Weeks (1/0) × Sophisticated (1/0)	-0.0002	7.96×10^{-5}
	(-0.1077)	(0.0183)
Window around Shock (1/0) × Sophisticated (1/0)	0.0199***	0.1407***
	(7.490)	(26.41)
After Shock Weeks (1/0) × Window around Shock (1/0)	0.0091***	0.0308***
	(14.09)	(25.33)
After Shock Weeks (1/0)	0.0010**	0.0040***
	(2.565)	(4.319)
Window around Shock (1/0)	0.0007	-0.0080***
	(1.163)	(-8.568)
N	21,303,667	21,303,667
R-squared	0.12	0.18
Person FE	Yes	Yes
Week × State × Income Class FEs	Yes	Yes

Table IA.V. Heterogeneous Investment Response to Temporary Positive Income Shocks Below-Median Income Investors

This table reports the heterogeneous difference in cryptocurrency and traditional investment before v. after a temporary positive income shock for below-median income investors. The window around shock is the T_{it} variable is equation (5), 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. 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)
After Shock Weeks (1/0) × Window around Shock (1/0) × Below-Median Income (1/0)	0.0032**	-0.0272***
	(2.506)	(-11.83)
After Shock Weeks (1/0) × Below-Median Income (1/0)	-0.0018**	-0.0005
	(-2.414)	(-0.2915)
Window around Shock (1/0) × Below-Median Income (1/0)	-0.0002	-0.0090***
	(-0.1727)	(-4.584)
After Shock Weeks (1/0) × Window around Shock (1/0)	0.0083***	0.0471***
	(10.23)	(27.38)
After Shock Weeks (1/0)	0.0017***	0.0043***
	(3.311)	(3.221)
Window around Shock (1/0)	0.0028***	0.0098***
	(3.825)	(7.973)
N	21,303,667	21,303,667
R-squared	0.12	0.18
Person FE	Yes	Yes
Week × State × Income Class FEs	Yes	Yes

Table IA.VI. Heterogeneous Investment Response to Temporary Positive Income Shocks Overdrafters

This table reports the heterogeneous difference in cryptocurrency and traditional investment before v. after a temporary positive income shock for overdrafters. The window around shock is the T_{it} variable is equation (5), 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. 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)
After Shock Weeks (1/0) × Window around Shock (1/0) × Overdrafter (1/0)	0.0029**	-0.0018
	(2.097)	(-0.6841)
After Shock Weeks (1/0) × Overdrafter (1/0)	-0.0006	-0.0026
	(-0.6612)	(-1.337)
Window around Shock (1/0) × Overdrafter (1/0)	0.0067***	0.0003
	(4.389)	(0.1152)
After Shock Weeks (1/0) × Window around Shock (1/0)	0.0085***	0.0387***
	(11.43)	(25.43)
After Shock Weeks (1/0)	0.0012**	0.0048***
	(2.567)	(4.136)
Window around Shock (1/0)	0.0007	0.0064***
	(1.034)	(5.660)
N	21,303,667	21,303,667
R-squared	0.12	0.18
Person FE	Yes	Yes
Week × State × Income Class FEs	Yes	Yes

Table IA.VII. 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.VIII. 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.IX. 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.X. 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.XI. 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.XII. 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.XIII. Definitions of Variables

Variable	Definition
Retail Investments and Returns	
Log Crypto Investment ($)	The natural logarithm of one plus the sum of all debits where merchant name or transaction description contains the name of a crypto trading venue (e.g., crypto exchange) in a given period (month or week, as appropriate)
Crypto Investment Likelihood (1/0)	Dummy for making a crypto deposit in a given period (month or week, as appropriate)
Log Traditional Investment ($)	The natural logarithm of 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 ($)	The natural logarithm of one plus the sum of all debits where the transaction category is "Securities trades," except where merchant name or transaction description contains the name of a FinTech brokerage, in a given period (month or week, as appropriate)
BTC Return (%)	Bitcoin return, represented by the percent change of Bitcoin price from the previous year to this year.
Income and Consumption	
% Chg Debits (%)	Percent change in the sum of all debits (i.e., deposits) for crypto or traditional investments in a given period (month or week, as appropriate)
% Chg Credits (%)	Percent change in the sum of all credits (i.e., withdrawals) for crypto or traditional investments in a given period (month or week, as appropriate)
% Chg Net Flows (%)	Percent change in the sum of all debits (i.e., deposits) minus the sum of all credits (i.e., withdrawals) for crypto or traditional investments in a given period (month or week, as appropriate)
Total Debits ($)	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
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 an 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
Permanent Positive Income Shock	Weeks where an individual experienced a positive income shock, and this new level is within a standard deviation from the average weekly salary in the next 6 months and the future 6 month average is *above* the past 12 month average
Temporary Positive Income Shock	Weeks where an individual experienced a positive income shock, and not a permanent positive income shock
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
Permanent Negative Income Shock	Weeks where an individual experienced a negative income shock, and this new level is within a standard deviation from the average weekly salary in the next 6 months and the future 6 month average is *below* the past 12 month average
Temporary Negative Income Shock	Weeks where an individual experienced a negative income shock, and not a permanent negative income shock
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