Disctracted by Crypto*

Matheus Brito † Fernando Chague ‡ Jefferson Colombo §

July 29, 2024

Abstract

How do retail equity investors responded to the surge in cryptocurrencies? Analyzing detailed data on all Brazilian investors from 2012 to 2018, we find that retail equity trading decreases during periods when cryptocurrencies are attention-grabbing. The economic impact ranges from 5.1% to 7.9%, and are more pronounced among younger investors and those in blockchain-related professions. Net trading flow analysis reveals no significant inflows or outflows, supporting a distraction-based interpretation. Validation with U.S. retail trading data confirms these results. As cryptocurrencies become mainstream from 2019 to 2022, we observe a diminishing distraction effect, consistent with individuals perceiving them as a regular asset.

*Chague and Brito gratefully acknowledge financial support from CNPq.

†Phd Student at Getulio Vargas Foundation - Sao Paulo School of Economics, Brazil. Email: matheus.brito@fgv.edu.br

‡Getulio Vargas Foundation - Sao Paulo School of Economics, Brazil. E-mail: fernando.chague@fgv.br.

§Getulio Vargas Foundation - Sao Paulo School of Economics, Brazil. E-mail: jefferson.colombo@fgv.br.

1 Introduction

Since its inception in 2009, Bitcoin has evolved from obscure beginnings to being traded on major stock exchanges through ETFs and futures contracts. Enthusiasts emphasize its potential hedging benefits and support its inclusion in diversified portfolios, making a case for cryptocurrencies as a new asset class in their own right. At the same time, regulators and academics warn that cryptocurrencies are speculative and prone to bubbles. But how has individual trading actually responded to the rapid surge of cryptocurrency in the investment scene? In this paper, we answer this question using detailed field data from retail trading in the stock market.

While there is some survey evidence on how individuals incorporate cryptocurrencies into their portfolios (for instance, Auer and Tercero-Lucas (2022), Weber, Candia, Coibion, and Gorodnichenko (2023), and (Benetton and Compiani, 2024)), evidence from actual trading decisions is scarce. The fact that cryptocurrencies are traded on separate and unregulated exchanges, detached from traditional financial markets, means that comprehensive data on complete portfolio holdings are not easily available.

To analyze the impact of cryptocurrencies on stock trading decisions, we first developed a crypto-salience indicator. Following the approach of (Barber and Odean, 2008), who measure daily attention to stocks by focusing on indicators like unusual trading volume, extreme returns, and news, we adapted a similar attention-grabbing measure for cryptocurrencies. This measure is constructed as the first principal component of three variables: changes in Bitcoin prices, abnormal Bitcoin trading volumes, and the intensity of Bitcoin-related discussions on the social media platform Reddit. Our analysis of this indicator reveals significant daily fluctuations. Notably, attention peaks coincide with major events in the cryptocurrency market during specific periods such as April 2013, November-December 2013, February 2014, January 2015, November-December 2017, January-February 2018, March 2020, January-February 2021, and May 2021.

We then examine whether cryptocurrencies attention-grabbing events had an effect on retail equity trading by analyzing daily trading data from all Brazilian investors from 2012 to 2018. Importantly, our dataset includes individual-level information such as age and profession, which has proven valuable in establishing a link between these attention-grabbing events and changes in equity trading behavior. We also examine aggregate retail trading in an extended sample from 2019 to 2022.

During the sample period from 2012 to 2018, our findings show that retail investors responded to attention-grabbing events by withdrawing from equity trading. The economic impact of these shifts is substantial, with reductions in retail trading activity ranging from 5.1% to 7.9%, depending on the specific metrics used to define this activity. This substitution pattern is consistent with the hypothesis that individual investors often engage in trading as an exciting and recreational gambling-like activity, suggesting an intentional substitution between stock trading and alternative gambling-like opportunities, as highlighted in Gao and Lin (2015) and Dorn, Dorn, and Sengmueller (2015).

Regarding the total number of active retail investors (those buying or selling any stock on a given day), our results shows that an increase of one standard deviation in our crypto-salience indicator correlates with a 7.9% decrease in the number of active retail investors, which translates to 1,606 individuals on a given day. In terms of total trading volume (buying plus selling), we observe a reduction of 6.0%, or approximately 820 million US dollars. Finally, when looking at the fraction of total trading volume attributed to retail investors, we find a 5.1% reduction. When we analyze buying and selling activities separately, we observe similar reductions in both, suggesting that there are no significant shifts of funds from equities to cryptocurrencies linked to the crypto-salience indicator. This pattern supports the distraction hypothesis.

Next, we examine whether the results are heterogeneous across investors. First, we separate investors by their age. We find that the reduction in retail trading is concentrated within younger individuals born in the 1970s, 1980s, or 1990s relative to those born earlier. Second, we separate individuals by their professions. We find that trading by those in professions more closely related to computing fields (engineering and system analysts) is more affected by attention-grabbing events. The fact that younger individuals and those in professions related to cryptocurrencies are more likely to experience crypto-salience shocks, and are also the ones who reduce their equity trading activity, is reassuring. This finding aligns with survey data indicating that such individuals are more likely to be interested in cryptocurrencies (Auer and Tercero-Lucas, 2022, Weber, Candia, Coibion, and Gorodnichenko, 2023).

We then examine which of the components of the crypto-salience indicator are the most important for our results. We run regressions of retail trading activity on each of the three variables that make up our indicator: bitcoin price changes, abnormal trading volume, and activity in the Reddit forum. We find that messages in the related Reddit forums and abnormal crypto trading activity are the most important variables driving our results.

We next run a number of robustness tests. An immediate concern is that our results are driven by a mechanical relation between messaging intensity in Reddit forums and trading activity. To rule out this possibility, we construct a stock-salience indicator also using Reddit subforums. Specifically, we count the number of times the word "stock" (or "stocks") is mentioned in r/WallStreetBets, the most famous subreddit forum about investments on Reddit. As expected, we find a reverse effect. An increase in our stock-salience indicator is accompanied by an increase in retail trading activity, and not by a decrease.

Another possible concern relates to the external validity of our results. Are our findings restricted to Brazilian investors? To answer this, we obtain a proxy of retail trading by US individuals using the algorithms developed by (Boehmer, Jones, Zhang, and Zhang, 2021a), which unveils a fraction of retail trading volume from marketable retail orders using consolidated TAQ (Trade and Quote) public data. Our findings are remarkably similar to the ones we documented using Brazilian data, although the economic magnitude is smaller. We find that an increase of one standard deviation in our crypto-salience indicator is followed by a 1.9% decrease in retail trading volume and also a 1.9% decrease in the fraction of total volume attributed to retail individuals.

Finally, we obtained a less detailed version of our dataset extending to 2022, which allows us to observe the total trading volume by retail investors, though it does not enable us to identify the number of individuals or analyze any demographic characteristics. When we conduct regressions on the extended series from 2012-2022, we find that the crypto-salience indicator is still negatively associated with retail trading activity, but the effect is weaker. Interestingly, in the later years, as examined through time-varying biannual rolling window regressions, the effects show an opposite sign. This period also coincides with the introduction of a cryptocurrency ETF on the Brazilian stock exchange, suggesting that individuals may react to it as they do to other conventional assets. Interestingly, this finding aligns with the evidence presented by (Popescu, 2023), who investigate returns and volatility spillovers among a representative set of crypto and financial assets. They find that spillover effects have intensified over time, reaching their peak during the COVID-19 pandemic, which indicates a growing interdependence of cryptocurrencies with traditional markets.

Our paper contributes to the rapidly growing literature on cryptocurrencies as a financial asset, with several studies utilizing survey data. Auer and Tercero-Lucas (2022) analyze data from the U.S. Survey of Consumer Payment Choice, finding that cryptocurrency investors are typically educated, young, and digital natives. They also note that a gender ownership gap in cryptocurrencies has emerged in recent years. Weber, Candia, Coibion, and Gorodnichenko (2023) examines a quarterly survey of U.S. households from the Nielsen Home-scan Panel, initiated in 2018, providing insights into the demographics of cryptocurrency investors, who are predominantly young and male. These investors cite the higher expected returns, diversification, and inflation-hedge benefits of cryptocurrencies as reasons for their investment. Benetton and Compiani (2024) use data from the Cryptocurrency and Blockchain Consumer and Investor Survey to show that younger individuals with lower incomes, as well as late investors, are more optimistic about the future value of cryptocurrencies.

In contrast, only a few studies examine actual trading decisions across both traditional asset classes and cryptocurrencies. Hackethal, Hanspal, Lammer, and Rink (2022) utilize administrative data from a random sample of customers at a large German online bank to explore the stock portfolio holdings of investors who also purchase cryptocurrency structured retail products. They find that these investors tend to trade stocks that are frequently in the media, have high past performance, and resemble lottery-like stocks. Kogan, Makarov, Niessner, and Schoar (2023) analyze 200,000 accounts from individual investors at eToro, one of the first platforms to allow trading of cryptocurrencies alongside traditional assets from 2015 to 2019. They observe that while retail investors seem to follow a momentum-like strategy in cryptocurrencies, they adopt a contrarian approach in stocks and gold. While these studies highlight within-trader differences in behavior across different asset types, our research focuses on how events in one asset class (cryptocurrencies) influence trading behavior in another.

Our paper also contributes to a growing body of literature exploring the effects of attention on retail trading. Barber and Odean (2008) find that attention-grabbing stocks are more likely to be purchased relative to other stocks. Using brokerage data, Barber, Huang, Odean, and Schwarz (2022) find that features in trading apps that enhance attention are effective in increasing retail trading volume. Arnold, Pelster, and Subrahmanyam (2022) find that push messages sent by stock brokers induce investors to increase their trading through increased risk-taking. Using the same Brazilian data that we use in this paper, Chague, Giovannetti, and Paiva (2022) find that stocks that are easier to recall are traded more frequently. Specifically, the authors find that brick-and-mortar firms that are listed on the exchange are more than two times more day-traded by retail investors if there is a local store nearby where the investor lives.

Another set of papers examines how retail investors' attention can also be diverted away from the equity market. Gao and Lin (2015) and Huang, Huang, and Lin (2019) document that retail trading volume decreases during periods when large lottery jackpots accumulate and become nationally salient events in Taiwan. Peress and Schmidt (2020) examines 551 episodes of sensational news unrelated to the stock market, such as the broadcast of the O.J. Simpson trial verdict by U.S. news, and finds that such distraction events effectively reduce stock trading activity by retail investors. In this paper, we find that the emergence of a new trading instrument with speculative features distracted individuals from equity trading.

The remainder of the paper is organized as follows. Section 2 describes the data and presents our crypto-salience indicator. Section 3 presents our main empirical results. Section 4 presents some robustness exercises. Finally, Section 5 concludes.

2 Data

Our dataset with retail trading comes from CVM ("Comissão de Valores Mobiliários"), the Brazilian equivalent of the Securities Exchange Commission in the United States. It contains the trading activity of all retail investors at the investor-stock-day level from 2012 to 2018 in the Brazilian stock exchange. In our dataset, each retail investor is identified by an unique anonymous id. We have information about the quantity purchased, quantity sold, volume purchased, and volume sold for each investor-stock-day triple. Additionally, we have ID-level information, including the gender and age of birth of the retail investor. Public information about firms, including market capitalization and stock prices adjusted for corporate events and dividend payouts, come from the Economática data provider. [1]

We calculate three measures of retail trading activity. The first measure is the total number of retail investors active in the equity markets on a given day (i.e., buying and/or selling at least one stock). The second measure is the total volume traded by retail investors (volume purchased plus volume sold) in millions of US dollars.[2] Finally, we compute the total volume traded by retail investors divided by the total volume traded by all investors.

During the sample period, 1,074,721 retail investors traded at least once, involving 787 different stocks. Table 1 presents descriptive statistics for the daily retail trading measures. Throughout our sample period, there were, on average, 20,332 distinct retail investors active on any given day, with an average total trading volume of US$820 million. On average, active retail trading represented 15.75% of the total trading volume, which is very similar to what we observe for US markets, for instance.[3]

[1] http://economatica.com/

[2] We use the average exchange rate during our sample period (R$/US$ 2.87) to convert values to US dollars

[3] https://www.nasdaq.com/articles/who-counts-as-a-retail-investor-2020-12-17

[Table 1 about here]

2.1 Crypto-salience measure

(Barber and Odean, 2008) find that retail investors are net buyers of attention-grabbing stocks. They define stocks as attention-grabbing when these stocks are prominently featured in the news, exhibit high abnormal trading activity, or experience extreme daily returns. Building on their idea, we propose a "crypto-salience" measure for cryptocurrencies. It's derived from three variables linked to attention-grabbing events from the standpoint of retail investors. The first variable is based on the level of discussion activity on the social media platform Reddit.[4] Specifically, we calculate the frequency of mentions of the words "Bitcoin" or "BTC" (the standard abbreviation for bitcoin) across the three most relevant forums dedicated to Bitcoin during our sample period: Bitcoin, BitcoinBeginners, and BitcoinMarkets. According to Table 1, there is an average of 1,182 daily mentions about Bitcoin across these three forums during our sample period.

The second variable is the daily return of Bitcoin, which is calculated using the median price across the primary Bitcoin trading platforms. The data is from the website https://data.bitcoinity.org/. We gather the daily average price from each of the following cryptocurrency trading platforms: BitX, Bitfinex, Bitstamp, Cex.io, Coinbase, Exmo, Gemini, Itbit, and Kraken. These platforms allow individuals to buy, sell, and trade various cryptocurrencies, including Bitcoin. Additionally, we have the average price from the remaining trading platforms surveyed by bitcoinity.org. The daily Bitcoin price we use is the median among the prices from these ten price sources. The average spread across trading

[4] Reddit is a social media platform and online community where users can submit content, such as text posts, links, images, and videos, which are then voted on by other members. It features a wide range of topics and discussions organized into "subreddits," each dedicated to a specific theme or interest.

platforms concerning the median price is 36 basis points.

The third variable aims to measure the intensity of Bitcoin trading on these platforms. We obtain the daily number of deals closed on all major Bitcoin trading platforms. Our variable is calculated as the daily number of deals closed in the major Bitcoin trading platforms, divided by the average of the same variable over the past year (i.e., from day t-252 to day t-1). We refer to this variable as "abnormal trading intensity."

All three variables are likely related to events that capture individuals' attention. To create a single measure of crypto-salience, we derive the first principal component from them. Figure 1 displays our crypto-salience measure alongside bitcoin prices from 2012 to 2018. It is evident that periods when cryptocurrencies are likely to capture attention correspond with significant bitcoin price fluctuations. In addition to significant daily variation, we observe some extreme episodes (exceeding three standard deviations of our measure), indicating that cryptocurrencies likely attracted extreme attention from individuals: April 2013, November-December 2013, February 2014, January 2015, November-December 2017, and January-February 2018.

[Figure 1 about here]

Next, we will explore how crypto-salience influences retail trading activity in equity markets.

3 Distracted by crypto

Attention is a limited resource, and investors have a finite amount of time to assess their investment options. Perhaps not surprisingly, given the magnitude of these constraints for retail investors, (Barber and Odean, 2008) find that retail investors focus on attention-grabbing stocks when selecting which stocks to trade. It is unclear if the same behavior occurs across asset classes. While some asset classes may attract more attention than others at certain times, there are fewer asset classes available compared to the number of stocks. Next, we empirically evaluate whether periods when cryptocurrencies attract the attention of retail investors coincide with changes in retail stock trading.

To formally evaluate our hypothesis, we regress various measures of aggregate retail trading activity on $CryptoSalience_t$ along with several control variables. More specifically, we estimate the following equation:

$$\begin{gathered} RetailTrading_t = \beta_1 CryptoSalience_t + \beta_2 MktRet_t + \beta_3 MktVolume_t + \\ \beta_4 MktVolatility_t + \gamma' X_t + \epsilon_t \end{gathered} \tag{1}$$

where $RetailTrading_t$ can represent three different measure of equity trading by retail investors: (i) $log(number_t)$, the log of the total number of retail investors active (i.e., buying and/or selling) in the equity markets on a given day t; (ii) $log(volume_t)$, the log of the total volume traded by retail investors (volume purchased plus volume sold) in millions of US dollars on a given day t; (iii) $fraction_t$, the total volume traded by retail investors divided by two times the total volume in the equity markets on a given day t. Additionally, we include the following controls: $MktRet_t$, the cumulative return of the Ibovespa[5] index from day t-5 to day t-1; $MktVolatility_t$, indicating the average daily range variation of the Ibovespa index from day t-5 to day t-1, calculated by dividing the difference between the daily maximum and minimum values by their average; $MktVolume_t$, representing the log of the daily total trading volume in millions of US dollars. To account for seasonality in retail trading

[5] Ibovespa is the most widely used stock index in Brazil.

as well as potential trends in the number of new investors in the Brazilian stock exchange, we include X_t, a vector that represents the following calendar controls: (i) day-of-the-week dummies, (ii) month dummies, and (iii) a time trend. β_1 is our parameter of interest. A negative estimate would indicate that when cryptocurrencies are attention-grabbing, equity trading diminishes, suggesting that retail investors may be distracted by cryptocurrencies.

The estimates of equation (1) are presented in Table 2. To account heteroskedasticity and autocorrelation in the error structure, we employ the Newey-West variance estimator with five lags. Across all measures of retail equity trading, the effects of $CryptoSalience_t$ exhibit similar qualitative characteristics—they are statistically and economically significant. In Column (2), which includes all controls, an increase of one standard deviation in $CryptoSalience_t$ (which is 1.13 according to Table 1) is associated with a decrease of 7.9% in the total number of active retail investors ($0.079 = 1.13 \times 0.070$). This translates to a reduction of approximately 1,606 individuals (assuming the unconditional average of 20,332 as shown in Table 1).

[Table 2 about here]

The results remain equally significant when considering the other two measures of retail trading activity. In Column (4), considering log of the total trading volume by retail investors, an increase of one standard deviation in $CryptoSalience_t$ leads to a decrease of 6.0% in retail trading activity ($0.060 = 1.13 \times 0.053$). This translates to a reduction of approximately 49.07 individuals (assuming the unconditional average of 819.34 million US dollars). Finally, in Column (6), considering the fraction implies that an increase of one standard deviation in $CryptoSalience_t$ results in a reduction of 0.80 percentage points in the retail trading as a fraction of total trading volume ($0.80 = 1.13 \times 0.710$), which is a 5.10% decrease relative to the unconditional average.

Next, we investigate whether the effects of *CryptoSalience* on retail equity trading are distributed across the entire sample period. To explore this, we estimate equation (1) using two-year rolling window samples. Panel A in Table 3 presents the results for the log of the total number of retail investors on a given day, Panel B for log of the total trading volume, and Panel C for the fraction of total volume attributed to retail investors.

[Table 3 about here]

Overall, the results show consistent qualitative patterns. The impact of *CryptoSalience* on retail equity trading seems to be consistent over the years across all measures of retail trading, as the point estimates are consistently negative across the sub-samples. Notably, the impact is particularly pronounced during the following pairs of years: 2012-2013, 2015-2016, and 2017-2018. Regarding the number of retail investors, in Panel A, the estimate of β_1 is highest for the 2015-2016 sample period, at -0.122, followed by the 2017-2018 sample period, with -0.073. For the volume by retail investors, in Panel B, the estimate of β_1 is highest for the 2015-2016 sample period, at -0.103, also followed by the 2017-2018 sample period, with -0.038. Finally, regarding the fraction by retail investors, in Panel C, the estimate of β_1 is highest for the 2015-2016 sample period, at -1.498, followed by the 2017-2018 sample period, with -0.670.

3.1 Heterogeneity across investors' ages

Cryptocurrencies represent a novel asset class, and not all individuals may be familiar with them. Furthermore, given the highly speculative nature of Bitcoin, even if investors were aware of it, not many would be willing to devote their attention to such a risky asset. Thus, it is reasonable to expect that *CryptoSalience* would affect individuals differently.

In this subsection, we estimate Equation 1 across distinct age groups. Younger investors tend to participate more in social media discussions and are often more aware of new technologies and asset classes. Therefore, we expect that younger individuals are more likely to be influenced by *CryptoSalience* compared to older individuals.

Among the 1,074,721 distinct retail investors who traded at least once during our study period, we the year of birth for 790,861 individuals[6]. We categorize these individuals into six different age groups based on the year of their birth. The "1940s" group comprises individuals who were 65 years old or older in 2015; the "1950s" group includes those who were 55 years old or older in 2015 but not in the previous group; the "1960s" group includes those who were 45 years old or older in 2015 but not in the previous groups; the "1970s" group includes those who were 35 years old or older in 2015 but not in the previous groups; the "1980s" group includes those who were 25 years old or older in 2015 but not in the previous groups; and finally, the "1990s" group includes individuals who were 25 years old or younger in 2015. The respective group sizes are 63,983 for the "1940s" group, 84,549 for the "1950s" group, 116,067 for the "1960s" group, 192,208 for the "1970s" group, 253,533 for the "1980" group, and 80,521 for the "1990s" group.

Table 4 presents the results. In Panel A, we examine the proportion of active retail investors in each age group relative to the total number of active retail investors on the same day. In Panel B, we examine the proportion of total trading volume attributed to investors in each age group relative to the total volume traded by all retail investors on the same day.

[Table 4 about here]

As expected, the estimates show that younger investors are more likely to be distracted

[6]This information is not mandatory and is self-reported; therefore, we do not have this information for all investors.

when cryptocurrencies are likely to be grabbing investors attention. Considering Panel A, the estimated coefficients on $CryptoSalience$ in the regressions for "1970s", "1980s", and "1990s" age groups are all negative. For the "1980s" group, for instance, an increase of one standard deviation in $CryptoSalience$ implies a 0.55% increase in the fraction of active retail investors born in the 1980s relative to the total number of active retail investors ($0.55 = 1.13 \times 0.483$). In contrast, the estimated coefficients in the regressions for the older investors, those the "1940s", "1950s", and "1960s" age groups, are positive. Despite the positive estimate, we find in unreported regressions that the actual number of older investors does not increase with $CryptoSalience$. Therefore, the statistically positive coefficients in columns (1), (2), and (3) are driven by the reduction in the total number of active retail investors, which is in the denominator of the independent variable.

In Panel B of Table 4, the estimated coefficients on $CryptoSalience$ are negative and statistically significant for the "1980s" and "1990s" age groups. For the "1980s" group, for instance, an increase of one standard deviation in $CryptoSalience$ implies a 0.22% increase in the fraction of trading volume by retail investors born in the 1980s relative to the total trading volume by all retail investors implies a 0.22% increase in the fraction of trading volume by retail investors born in the 1980s relative to the total trading volume by all retail investors ($0.22 = 1.13 \times 0.194$).

3.2 Heterogeneity across investors' professions

In this section, we examine how our findings vary across professions. Among the 1,074,721 distinct retail investors who traded at least once during our study period, we have information about the profession of 790,861 individuals. The top 15 most reported professions, in terms of numbers, are as follows: 1) Engineer (a total of 76,489 individuals), 2) Administrator (63,524), 3) Banker (43,398), 4) Systems Analyst (38,136), 5) Doctor (31,309), 6) Retiree (28,492), 7) Entrepreneur (28,267), 8) Lawyer (26,977), 9) Federal Public Servant (24,592), 10) Student (18,417), 11) Manager (17,002), 12) State Public Servant (16,914), 13) Accountant (13,127), 14) Company Director (12,622), and 15) Economist (12,511).

Based on these 15 professions, we arbitrarily create 6 groups of professions that share similarities. In Group 1, we have Engineers and System Analysts, totaling 114,625 individuals. Group 2 consists of Students, totaling 18,417 individuals. In Group 3, we have Federal Public Servants and State Public Servants, totaling 41,506 individuals. In Group 4, we have Accountants, Administrators, Company Directors, Bankers, Entrepreneurs, and Managers, totaling 177,940 individuals. In Group 5, we have Doctors, Economists, and Lawyers, totaling 58,286 individuals. Lastly, Group 6 consists Retirees, totaling 45,493 individuals. The total number of individuals in these six groups is 439,266.

Table 5 presents the estimates of Equation (1) for each of the six groups. As before, Panel A examines the proportion of active retail investors in each age group relative to the total number of active retail investors on the same day, and Panel B examines the proportion of total trading volume attributed to investors in each age group relative to the total volume traded by all retail investors on the same day.

[Table 5 about here]

According to Panel A of Table 5, the estimates indicate that groups 1 and 2 are more likely to be distracted when cryptocurrencies are prominent. These groups include professions more closely related to computing fields (engineering and System Analysts) and younger professionals (students). For "Group 1" that includes Engineers and System Analysts, for instance, an increase of one standard deviation in $CryptoSalience$ implies an increase of 0.09

percentage points in the fraction of active retail investors from that group relative to the total number of active retail investors ($0.09 = 1.13 \times 0.079$). This represents a change of 0.6% relative to the unconditional average of this fraction ($0.6\% = 0.09/14.76\%$).

Considering "Group 2", that includes students, an increase of one standard deviation in *CryptoSalience* implies an increase of 0.03 percentage points in the fraction of active retail investors from that group relative to the total number of active retail investors ($0.03 = 1.13 \times 0.026$). In economical terms, this effect is stronger, since it represents a change of 3.1% relative to the unconditional average of this fraction ($3.1\% = 0.03/0.96\%$).

In Column (1) in Panel B, an increase of one standard deviation in *CryptoSalience* implies an increase of 0.09 percentage points in the fraction of active retail investors from that group relative to the total number of active retail investors ($0.16 = 1.13 \times 0.147$). Interestingly, the estimates are also negative and statistically significant in both panels for Group 3, which includes public servants.

In contrast, individuals working in more traditional professions, such as business, healthcare, economics, and law professionals, as well as retirees, seem to trade in the opposite direction during periods of crypto salience. According to Panel A of Table 5, the estimates on *CryptoSalience* for groups 4, 5, and 6 are all positive in both panels (except for Group 5 in Panel B).

3.3 Buying and selling

In this study, we have thus far analyzed total retail trading by summing the total volume purchased and the total volume sold. In this section, we investigate whether there are differential responses in trading volume between buying and selling. For example, if we observe a higher selling volume compared to buying volume, it may indicate that investors are reallocating their portfolios across asset classes, rather than solely being influenced by distractions related to cryptocurrencies. Consequently, we proceed to disaggregate our analysis based on retail buying and selling activities.

Table 6 presents the estimates of Equation (1) using the same retail trading measures, now focusing on buying only in Panel A, selling only in Panel B, and the difference between buying and selling in Panel C. Both buying and selling activities are found to be negatively affected by $CryptoSalience$, with similar magnitudes. For instance, considering only buying and all controls in Panel A, a one-standard deviation increase in $CryptoSalience$ is associated with a decrease of 8.1% in the total number of active retail investors who are buying stocks ($0.081 = 1.13 \times 0.072$), a 6.2% decrease in buying volume ($0.062 = 1.13 \times 0.055$), and a 0.81 percentage point decrease in retail trading as a fraction of total selling volume ($0.81 = 1.13 \times 0.718$). Similarly, considering only selling and all controls in Panel B, the decreases are 7.8%, 5.8%, and 0.79 percentage points, respectively, for the number of selling individuals, selling volume, and the fraction of total selling volume. Notably, all coefficients in Panel C are insignificantly different from zero, suggesting a symmetrical response of retail buying and selling to $CryptoSalience$.

[Table 6 about here]

3.4 Inside the crypto-salience measure

Our measure of crypto-salience is the first principal component from three variables that, individually, are likely to reflect episodes when cryptocurrencies are grabbing individuals attention. In this section, we examine the role each individual variable plays in our findings.

More specifically, we estimate Equation (1) replacing the variable $CryptoSalience_t$ by the variables: $BitcoinReddit_t$ refers to the frequency of mentions of the words "Bitcoin" or "BTC" in Reddit forums, $BitcoinReturn_t$, the daily return of Bitcoin calculated using the median price across the major Bitcoin trading platforms, and $BitcoinTrading_t$, which capture abnormal trading in Bitcoin and is computed as the daily number of deals closed in the major bitcoin trading platforms divided by the average of the same variable over the past year (i.e. from day t-252 to day t-1).

Panel A in Table 7 presents the results for the number of retail investors, Panel B for the volume, and Panel C for the fraction of total volume attributed to retail investors. Overall, while all point estimates are individually negative, only those for $BitcoinReddit_t$ and $BitcoinTrading_t$ are statistically different than zero. Moreover, in all columns (4), both variables retain their statistical significance even when included at the same time, indicating that both provide relevant pieces of information.

[Table 7 about here]

Considering the number of retail investors in Panel A, the coefficient on $BitcoinReddit_t$ in Column (1) indicates that an increase of one standard deviation in the number of Bitcoin mentions in Reddit forums reduces the number of retail investors by 1,491 ($1,491 = 1,108 \times 1.346$). Similarly, in Column (3), an increase of one standard deviation in $BitcoinTrading_t$ reduces the number of retail investors by 1,395 ($1,395 = 1.30 \times 10.728 \times 100$).

Considering the number of retail investors in Panel B, the coefficient on $BitcoinReddit_t$ in Column (1) indicates that an increase of one standard deviation in the number of Bitcoin mentions in Reddit forums reduces the volume by retail investors by million US dollars ($45.23 = 1,108 \times 4.082/100$). Similarly, in Column (3), an increase of one standard deviation in $BitcoinTrading_t$, reduces the volume by retail investors by 46.18 million US dollars ($46.18 = 1.30 \times 35.526$).

Considering the number of retail investors in Panel C, the coefficient on $BitcoinReddit_t$ in Column (1) indicates that an increase of one standard deviation in the number of Bitcoin mentions in Reddit forums reduces the fraction traded by retail investors by 0.76 percentage points ($0.76 = 1,108 \times 0.069/100$). Similarly, in Column (3), an increase of one standard deviation in $BitcoinTrading_t$,reduces the fraction traded by retail investors by 0.74 percentage points ($0.74 = 1.30 \times 0.568$).

4 Robustness exercises

4.1 External validity: retail trading

It is a plausible concern that peculiarities about Brazilian investors and the Brazilian stock market might be driving our results. While this in itself would not be problematic, it could certainly limit the scope of our findings. To investigate this, we first assess whether Brazilian individuals are particularly attracted to cryptocurrencies in a manner that differs from, for example, the US. Indeed, in some countries where capital controls are significant, cryptocurrencies are typically very popular.

To evaluate this, we obtain data from Google Trends on the search intensity for the term ”Bitcoin” from computers located in Brazil, the U.S., and worldwide. Figure 2 displays this data from 2012 to 2018. As we can observe, the behavior and intensity of Google searches for Bitcoin are remarkably similar in Brazil and in the US.

[Figure 2 about here]

Next, we replicate our main results for the total volume of US retail trading. (Boehmer, Jones, Zhang, and Zhang, 2021b) propose a method to identify retail trading flow using publicly available U.S. equity transactions data. According to the authors, most marketable equity orders initiated by retail investors are executed by wholesalers or within the broker and by regulation these orders must have subpenny price improvements. The same subpenny price improvements are not available to institutions, which is how one can identify marketable retail orders using consolidated TAQ (Trade and Quote) public data. The authors claim their methodology applies well for the period from 2010 up until 2015, although they also examine flows until 2017 in an internet appendix.

We replicate the methodology in (Boehmer, Jones, Zhang, and Zhang, 2021b) and obtain a measure of the total volume[7] of marketable orders by retail investors in the U.S. stock market from 2012 to 2017. We also compute the fraction of total volume attributed to retail trading. We then regress these two measures of retail trading activity, total volume by retail investors and fraction of total volume, on $CryptoSalience_t$.

According to our estimates, the daily average of the total volume of marketable orders by retail investors in the U.S. stock market from 2012 to 2017 was $10,462$ million dollars, with a median of $10,254$ million dollars and a standard deviation of $2,154$ million dollars. The daily average of the fraction of total volume attributed to retail marketable volume was 10.83%, with a median of 10.69% and a standard deviation of 1.03%.

As before, we include the following controls: $MktRet_t^{US}$, the cumulative return of the SP500 index from day t-5 to day t-1; $MktVolatility_t^{US}$, indicating the average daily range variation of the SP500 index from day t-5 to day t-1, calculated by dividing the difference between the daily maximum and minimum values by their average; $MktVolume_t^{US}$, representing the daily total trading volume in millions of US dollars; and the calendar controls:

[7]The daily volume purchased plus the daily volume sold across all common stocks with share code 10 or 11 that were listed in the exchanges NYSE, Nasdaq, and NYSE American (former Amex). We excluded stocks with an average price of five or below during our sample period.

day-of-the-week dummies, month dummies, and a time trend. To account heteroskedasticity and autocorrelation in the error structure, we employ the Newey-West variance estimator with five lags.

Table 8 displays the results. As we can see, across the two measures of retail equity trading, the effects of $CryptoSalience_t$ on retail trading is negative. In Column (2), considering total trading volume, an increase of one standard deviation in $CryptoSalience_t$ leads to a decrease of \$198 million US dollars ($198 = 1.13 \times 176.07$), which is a 1.9% decrease relative to the unconditional average ($0.019 = 198/10,462$). Column (4), considering the fraction implies that an increase of one standard deviation in $CryptoSalience_t$ results in a reduction of 0.21 percentage points in the retail trading as a fraction of total trading volume ($0.21 = 1.13 \times 0.190$), which is also a 1.9% decrease relative to the unconditional average ($0.019 = 0.21/10.83$).

[Table 8 about here]

4.2 Placebo: Stock-salience and retail investors trading

A crucial component of our crypto-salience measure is derived from the social media platform Reddit. One potential concern is that the posting frequency in this social media might be influenced by mechanical reasons unrelated to attention-grabbing cryptocurrency events, leading to the possibility that our findings are spurious. To address these concerns, we now compute a $StockSalience_t$ variable that is the frequency of the word "stock" (or "stocks") on the most popular investment forum on Reddit: r/Wallstreetbets. [8] If there are mechanical factors related to Reddit posting frequencies influencing our results, we should also observe

[8] r/Wallstreetbets is a subreddit forum known for its discussions on high-risk stock trading, which gained widespread notoriety during the GameStop episode in 2021.

a negative coefficient β_1 when estimating the equation. 1.

The average value of $StockSalience_t$ during our sample period is 84.67, with a standard deviation of 109.82 and a median value of 38.5. As shown in Table 2, retail trading is actually higher when this measure of $StockSalience_t$ increases. In Column (2), an increase of one standard deviation in $StockSalience_t$ (which amounts to 109.82) is associated with an increase of 4,403 in the number of active retail investors ($4,403 = 109.82 \times 0.401 \times 100$). This represents a significant increase of 21.7% compared to the average number of active retail investors on any given day (20,332 according to Table 1).

The conclusion is the same with the other two measures of retail trading. In Column (4), when considering total trading volume, an increase of one standard deviation in $StockSalience_t$ leads to a decrease of 163.85 million US dollars ($163.85 = 109.82 \times 1.492$), representing a 20.0% increase relative to the unconditional average. Finally, in Column (6), when considering the fraction, an increase of one standard deviation in $StockSalience_t$ results in a reduction of 1.10 percentage points in retail trading as a fraction of total trading volume ($1.10 = 109.82 \times 0.010$), indicating a 6.98% decrease relative to the unconditional average.

The fact that retail trading activity increases whenever stocks are grabbing individuals attention is consistent with findings presented by Barber and Odean, 2008.

[Table 9 about here]

4.3 Fixing the number of investors

During our sample period, the total number of active retail investors exhibited a positive trend. To check the robustness of our findings to a change in the trading population, in this section, we reestimate our main tables using only individuals who were already active in the first semester of 2012. Specifically, we calculate all retail trading measures assuming that the only investors in the Brazilian stock market are those who executed at least one deal during the first six months of 2012. Then, we estimate Equation (1), excluding these first six months from our regressions.

Table 10 show the results. As before, the results for all three measures of retail equity trading from individuals already active in 2012 indicate that whenever cryptocurrencies attract retail investors' attention, we observe a reduction in equity trading. In Column (2), which incorporates all controls, an increase of one standard deviation in $CryptoSalience_t$ is linked to a decrease of 572 in the daily number of active retail investors ($572 = 1.13 \times 5.064 \times 100$). In Column (4), considering total trading volume, an increase of one standard deviation in $CryptoSalience_t$ leads to a decrease of $22.38 million US dollars ($22.38 = 1.13 \times 19.807$). Finally, in Column (6), considering the fraction implies that an increase of one standard deviation in $CryptoSalience_t$ results in a reduction of 0.42 percentage points in the retail trading as a fraction of total trading volume ($0.42 = 1.13 \times 0.373$).

[Table 10 about here]

4.4 Extended sample period: 2012-2022

Cryptocurrencies have become increasingly popular recently, particularly following the significant increase in Bitcoin prices observed in 2021. Furthermore, it has become much easier for equity traders to invest in cryptocurrencies with the surge of cryptocurrency ETFs.[9] To explore the impact of these recent changes on our results, we expanded our original dataset

[9] The evolution of cryptocurrency ETFs has been remarkable in recent years. The launch of the first Bitcoin ETF in Canada in 2021 marked a significant milestone, providing investors with a regulated way to invest in Bitcoin through traditional brokerage accounts.

to include aggregated retail trading from 2019 to 2022. This addition allows us to examine the overall trading volume by retail investors and the percentage of total volume they account for. However, we do not observe the number of retail investors, not any individual characteristics like age and profession.

An analysis of *CryptoSalience* spanning the 2012-2022 period highlights additional high attention-grabbing events (defined as days exceeding three standard deviations of our measure) occurring in March 2020, January-February 2021, and May 2021, in addition to those previously identified in April 2013, November-December 2013, February 2014, January 2015, November-December 2017, and January-February 2018.

Table 11 presents the results. We now have a total of 2,217 trading days in our sample that goes from 2012 to 2022. Overall, the results are consistent with our previous findings: on days when cryptocurrencies attract attention, there is also a significant decrease in retail equity trading activity. In Column (2) with all the controls and considering the log of the total trading volume by retail investors, an increase of one standard deviation in $CryptoSalience_t$ leads to a decrease of 2.9% in retail trading activity ($0.029 = 1.15 \times 0.025$). In Column (4) also with all the controls but considering the fraction of total volume by retail investors, an increase of one standard deviation in $CryptoSalience_t$ results in a reduction of 0.40 percentage points in the retail trading as a fraction of total trading volume ($0.400 = 1.15 \times 0.344$).

[Table 11 about here]

Although the direction remains the same, the economic impact has diminished. To understand why and when this change occurred, we analyzed the regression using biannual rolling windows from 2012 to 2022. Table 12 presents the results. Interestingly, starting in 2021, the relationship between cryptocurrency and equity trading reversed. Notably, an increase in $CryptoSalience_t$ is associated with an increase in retail equity trading in the latter two years of the extended sample. This shift coincides with the launch of a new ETF listed on the Brazilian stock exchange, which tracks the Hashdex Nasdaq Crypto Index and has gained popularity among Brazilian investors. These developments have helped establish cryptocurrencies as a new investment category, rather than solely speculative assets.

[Table 12 about here]

5 Conclusion

Our shows how significant events within the cryptocurrency market influence traditional retail trading behaviors. Throughout our analysis, from 2012 to 2022, we observe that attention-grabbing events in cryptocurrencies have a real impact on retail equity trading, leading to a substantial reduction in activity during peaks of crypto attention. This pattern is consistent with a shift in investor attention and resources, as individuals are distraction away from traditional equities toward emerging digital assets.

Interestingly, as the crypto market matures, and especially with the introduction of cryptocurrency financial products like ETFs, these effects appear to reverse. This shift suggests an integration of cryptocurrencies into more conventional investment strategies.

References

Arnold, Marc, Matthias Pelster, and Marti G. Subrahmanyam, 2022, Attention triggers and investors risk-taking, *Journal of Financial Economics* 143, 846–875.

Auer, Raphael, and David Tercero-Lucas, 2022, Distrust or speculation? The socioeconomic drivers of U.S. cryptocurrency investments, *Journal of Financial Stability* 62, 101066.

Barber, Brad M., Xing Huang, Terrance Odean, and Christopher Schwarz, 2022, AttentionâInduced Trading and Returns: Evidence from Robinhood Users, *The Journal of Finance* 77, 3141–3190.

Barber, Brad M., and Terrance Odean, 2008, All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors, *Review of Financial Studies* 21, 785–818.

Benetton, Matteo, and Giovanni Compiani, 2024, Investors' Beliefs and Cryptocurrency Prices, *Review of Asset Pricing Studies* raad015.

Boehmer, Ekkehart, Charles M. Jones, Xiaoyan Zhang, and Xinran Zhang, 2021a, Tracking Retail Investor Activity, *The Journal of Finance* 76, 2249–2305.

Boehmer, Ekkehart, Charles M. Jones, Xiaoyan Zhang, and Xinran Zhang, 2021b, Tracking Retail Investor Activity 76, 2249–2305.

Chague, Fernando, Bruno Giovannetti, and Guilherme Paiva, 2022, Out of sight, out of mind: Local stores and retail day-trading, *Working Paper* .

Dorn, Anne Jones, Daniel Dorn, and Paul Sengmueller, 2015, Trading as Gambling, *Management Science* 61, 2376–2393.

Gao, Xiaohui, and Tse-Chun Lin, 2015, Do Individual Investors Treat Trading as a Fun and Exciting Gambling Activity? Evidence from Repeated Natural Experiments, *Review of Financial Studies* 28, 2128–2166.

Hackethal, Andreas, Tobin Hanspal, Dominique M Lammer, and Kevin Rink, 2022, The Characteristics and Portfolio Behavior of Bitcoin Investors: Evidence from Indirect Cryptocurrency Investments*, *Review of Finance* 26, 855–898.

Huang, Shiyang, Yulin Huang, and Tse-Chun Lin, 2019, Attention allocation and return co-movement: Evidence from repeated natural experiments, *Journal of Financial Economics* 132, 369–383.

Kogan, Shimon, Igor Makarov, Marine Niessner, and Antoinette Schoar, 2023, Are Cryptos Different? Evidence from Retail Trading, *Nber Working Paper* .

Peress, Joel, and Daniel Schmidt, 2020, Glued to the TV: Distracted Noise Traders and Stock Market Liquidity, *The Journal of Finance* 75, 1083–1133.

Popescu, Roshan Iyer, Adina, 2023, New Evidence on Spillovers Between Crypto Assets and Financial Markets.

Weber, Michael, Bernardo Candia, Olivier Coibion, and Yuriy Gorodnichenko, 2023, Do You Even Crypto, Bro? Cryptocurrencies in Household Finance, *Nber Working Paper* .

Figures

Figure 1: Crypto-salience and Bitcoin prices

The top graph shows a metric capturing when cryptocurrencies are likely to attract attention. It combines three variables: (i) the daily frequency of "bitcoin" mentions on Reddit, (ii) the daily bitcoin return, and (iii) the daily abnormal trading intensity of bitcoin on major exchanges. This composite measure, that we call crypto-salience, is calculated as the first principal component of these variables. The lower graph shows the logarithm of Bitcoin prices in US dollars.

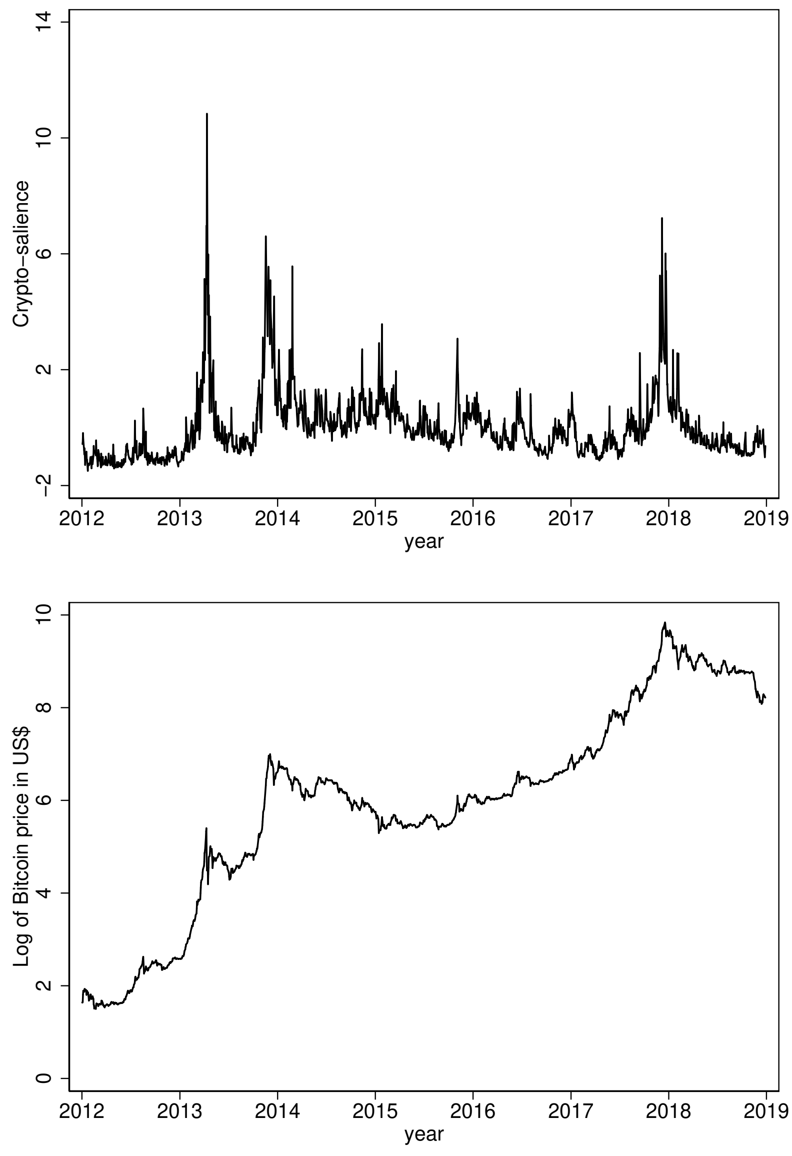
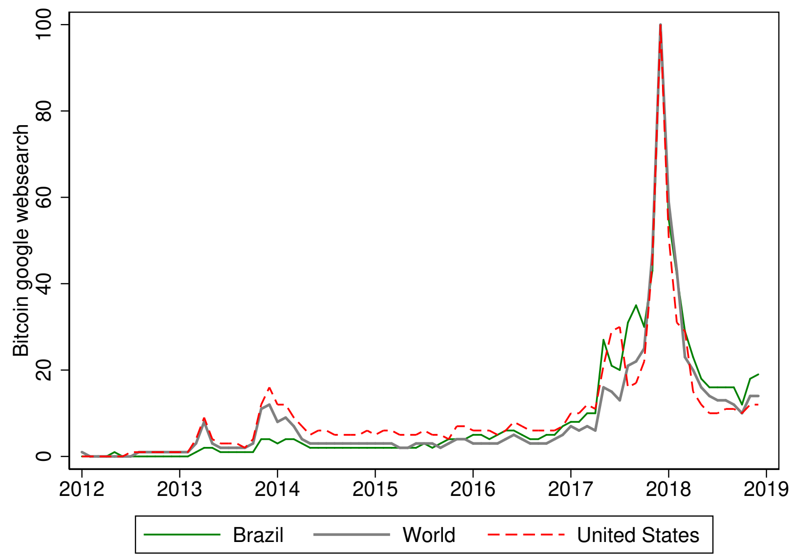


Figure 2: Google web search index for the term "Bitcoin"

This figure displays the Google web search index for the term "Bitcoin" on computers located in Brazil, the US, and worldwide from 2012 to 2018. The source is Google Trends (https://trends.google.com.br/trends/).



Tables

Table 1: Descriptive statistics

This table displays the mean, standard deviation, and percentiles 1, 25, 50, 75, and 99 of the variables used in the regressions; all variables are daily and cover the period from 2012 to 2018. *Bitcoin in social media* refers to the frequency of mentions of the words "Bitcoin" or "BTC" across the following Subreddit forums: Bitcoin, BitcoinBeginners, and BitcoinMarkets. *Bitcoin return* is the daily return of Bitcoin calculated using the median price across the major Bitcoin trading platforms. *Bitcoin trading* is the daily number of deals closed in the major bitcoin trading platforms, divided by the average of the same variable over the past year (i.e. from day t-252 to day t-1). *Crypto-salience* is the first principal component computed from the preceding three variables. *Number of retail investors* is the total number of retail investors active (i.e., buying and/or selling) in the equity markets on a given day. *Volume by retail investors* is the total volume traded by retail investors (volume purchased plus volume sold) millions of US dollars. *Fraction by retail investors* is the total volume traded by retail investors divided by two times the total volume in the equity markets. *Market return* is the cumulative returns of the Ibovespa over the past five trading days. *Market volatility* is calculated as the 5-day average of the daily range variation of the Ibovespa index, which is obtained by dividing the difference between the daily maximum and minimum values by the average of the two. *Market volume* is the daily total volume in millions of US dollars.

	Mean	Std. Dev.	pct1	pct25	pct50	pct75	pct99
Bitcoin in social media	1,182	1,108	30	565	977	1,449	5,518
Bitcoin return	0.00	0.05	-0.11	-0.01	0.00	0.02	0.17
Bitcoin abnormal trading	1.41	1.30	0.05	0.61	1.10	1.82	6.46
Crypto-salience	0.00	1.13	-1.32	-0.70	-0.25	0.38	5.03
Number of retail investors	20,332	8,106	10,206	14,600	18,028	24,266	49,208
Volume by retail investors	819.34	328.15	365.85	596.86	735.29	966.81	1,957.82
Fraction by retail investors	15.75	3.23	6.02	13.66	15.62	17.80	23.84
Market return	0.20	2.71	-6.18	-1.53	0.23	2.01	6.95
Market volatility	1.92	0.60	0.93	1.51	1.80	2.21	3.81
Market volume	5,314.24	2,256.22	2,211.16	3,999.39	4,751.73	5,926.70	14,383.25
Observations	1727						

Table 2: Crypto-salience and retail equity trading

The table displays regressions of daily retail equity trading activity on a daily proxy for crypto salience and control variables. *Number* is the log of the total number of retail investors active (i.e., buying and/or selling) in the equity markets on a given day. *Volume* is the log of total volume traded by retail investors (volume purchased plus volume sold) millions of US dollars. *Fraction* is the total volume traded by retail investors divided by two times the total volume in the equity markets. *Crypto-salience* is the first principal component computed from three variables: (i) the frequency of mentions of the words "Bitcoin" or "BTC" across Subreddit forums, (ii) the daily return of Bitcoin, (iii) the abnormal trading intensity in the major Bitcoin trading platforms. As controls, we include: *Market return*, the cumulative returns of the Ibovespa over the past five trading days; *Market volatility*, the 5-day average of the daily range variation of the Ibovespa index; *Market volume*, log of the daily total volume in millions of US dollars; and a number of calendar controls: (i) day-of-the-week dummies, (ii) month dummies, and (iii) a time trend. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	log(number)		log(volume)		fraction	
	(1)	(2)	(3)	(4)	(5)	(6)
Crypto-salience	-0.081***	-0.070***	-0.068***	-0.053***	-0.722***	-0.710***
	(-4.85)	(-5.49)	(-4.20)	(-5.06)	(-5.27)	(-5.32)
Market returns		0.014***		0.011***		0.164***
		(5.01)		(4.67)		(4.83)
Market volume		0.512***		0.717***		
		(18.59)		(25.64)		
Market volatility		-0.077***		-0.048***		-0.950***
		(-5.18)		(-3.98)		(-5.72)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.46	0.69	0.37	0.75	0.22	0.27
Observations	1727	1727	1727	1727	1727	1727

Table 3: Crypto-salience and retail equity trading across two-year samples

The table displays regressions of daily retail equity trading activity on a daily proxy for crypto salience and control variables across two-year rolling window samples. In Panel A, retail equity trading activity is the log of the total number of retail investors active (i.e., buying and/or selling) in the equity markets on a given day. In Panel B, the log of the total volume traded by retail investors (volume purchased plus volume sold) millions of US dollars. In Panel C, the total volume traded by retail investors divided by two times the total volume in the equity markets. *Crypto-salience* is the first principal component computed from three variables: (i) the frequency of mentions of the words "Bitcoin" or "BTC" across Subreddit forums, (ii) the daily return of Bitcoin, (iii) the abnormal trading intensity in the major Bitcoin trading platforms. As controls, we include: *Market return*, the cumulative returns of the Ibovespa over the past five trading days; *Market volatility*, the 5-day average of the daily range variation of the Ibovespa index; *Market volume*, log of the daily total volume in millions of US dollars; and a number of calendar controls: (i) day-of-the-week dummies, (ii) month dummies, and (iii) a time trend. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: log(number of retail investors)						
crypto-salience	-0.024***	-0.022**	-0.029***	-0.122***	-0.003	-0.073***
	(-4.34)	(-2.16)	(-2.91)	(-4.90)	(-0.20)	(-6.72)
market returns	0.013***	0.008**	0.007**	0.019***	0.013***	0.012***
	(3.70)	(2.06)	(2.54)	(4.36)	(3.14)	(3.84)
log(market volume)	0.262***	0.355***	0.301***	0.393***	0.473***	0.572***
	(7.45)	(8.79)	(8.24)	(8.04)	(9.13)	(21.39)
market volatility	-0.005	-0.038*	-0.002	-0.017	-0.100***	0.015
	(-0.30)	(-1.69)	(-0.13)	(-0.53)	(-4.03)	(0.97)
calendar controls	yes	yes	yes	yes	yes	yes
adjusted R-squared	0.44	0.34	0.38	0.44	0.62	0.77
observations	493	496	494	495	495	491
Panel B: log(volume by retail investors)						
Crypto-salience	-0.026***	-0.009	-0.008	-0.103***	-0.004	-0.038***
	(-4.13)	(-1.08)	(-0.79)	(-4.59)	(-0.27)	(-4.39)
Market returns	0.008*	0.008***	0.011***	0.016***	0.011***	0.007**
	(1.81)	(2.67)	(4.17)	(4.43)	(3.44)	(2.16)
Market volume	0.488***	0.590***	0.555***	0.616***	0.640***	0.774***
	(10.70)	(11.66)	(10.64)	(11.87)	(14.20)	(31.01)
Market volatility	0.041**	0.015	0.006	-0.019	-0.054***	0.024
	(2.06)	(0.86)	(0.32)	(-0.70)	(-2.86)	(1.56)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.59	0.63	0.65	0.61	0.75	0.82
Observations	493	496	494	495	495	491

continuous next page...

... continuous from previous page

	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: log(fraction by retail investors)						
Crypto-salience	-0.400***	-0.107	-0.064	-1.498***	-0.148	-0.670***
	(-4.81)	(-1.06)	(-0.65)	(-4.68)	(-0.75)	(-4.52)
Market returns	0.121**	0.103***	0.155***	0.239***	0.187***	0.113*
	(2.09)	(2.62)	(4.83)	(4.40)	(3.61)	(1.95)
Market volume	-6.026***	-4.212***	-4.565***	-4.527***	-5.351***	-4.039***
	(-14.76)	(-12.00)	(-13.60)	(-7.35)	(-10.74)	(-9.51)
Market volatility	0.532*	0.151	0.047	-0.487	-0.890***	0.451*
	(1.83)	(0.69)	(0.20)	(-1.19)	(-2.99)	(1.70)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.56	0.41	0.53	0.35	0.49	0.40
Observations	493	496	494	495	495	491

Table 4: Crypto-salience and retail equity trading for different ages

The table displays regressions of the daily retail investors trading activity among retail investors, organized by age group, using a daily proxy for the prominence of cryptocurrencies and control variables. The age groups are defined as follows: the "1940s" category includes individuals who were 65 years old or older in 2015; "1950s" includes those who were 55 years old or older in 2015 but not in the previous group; "1960s" includes those who were 45 years old or older in 2015 but not in the previous groups; and so on, with "1990s" referring to individuals who were 25 years old or younger in 2015. Panel A computes each subgroup's trading activity as the fraction of active investors from that subgroup over the total number of active retail investors each day. Panel B uses trading volumes instead. *Crypto-salience* is the first principal component computed from three variables: (i) the frequency of mentions of the words "Bitcoin" or "BTC" across Subreddit forums, (ii) the daily return of Bitcoin, (iii) the abnormal trading intensity in the major Bitcoin trading platforms. We include the same controls as in Table 2. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	1940s	1950s	1960s	1970s	1980s	1990s
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fraction of retail investors (number)						
Crypto-salience	0.335***	0.342***	0.168***	-0.185***	-0.483***	-0.176***
	(4.72)	(5.49)	(4.72)	(-4.50)	(-5.22)	(-3.96)
Market returns	-0.001	-0.009	-0.008	-0.030**	0.037	0.010
	(-0.07)	(-0.58)	(-0.86)	(-2.31)	(1.54)	(0.98)
Market volume	-0.003**	-0.008***	-0.011***	-0.003**	0.012***	0.014***
	(-2.00)	(-4.23)	(-6.49)	(-2.16)	(4.23)	(5.72)
Market volatility	-0.150*	-0.013	0.137***	0.162***	-0.013	-0.123**
	(-1.83)	(-0.16)	(3.05)	(2.64)	(-0.11)	(-2.21)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.91	0.92	0.92	0.57	0.94	0.88
Observations	1604	1604	1604	1604	1604	1604
Panel B: Fraction of retail investors (volume)						
Crypto-salience	0.093	0.096	0.108	0.025	-0.194***	-0.129***
	(1.24)	(1.39)	(1.35)	(0.35)	(-2.85)	(-4.84)
Market returns	0.076***	0.002	-0.028	-0.061**	-0.002	0.014*
	(3.34)	(0.08)	(-1.02)	(-2.56)	(-0.11)	(1.69)
Market volume	0.021***	0.005*	0.004	-0.017***	-0.018***	0.005***
	(5.78)	(1.72)	(0.94)	(-4.06)	(-5.66)	(4.58)
Market volatility	-0.767***	-0.113	0.865***	0.606***	-0.298**	-0.293***
	(-7.42)	(-1.06)	(6.33)	(4.49)	(-2.56)	(-6.24)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.49	0.51	0.46	0.35	0.81	0.59
Observations	1604	1604	1604	1604	1604	1604

Table 5: Crypto-salience and retail equity trading for different professions

The table displays regressions of daily trading activity among retail investors, grouped by professions, using a daily proxy for the prominence of cryptocurrencies and control variables. In Group 1, we have Engineers and System Analysts, totaling 114,625 individuals. Group 2 consists of Students, totaling 18,417 individuals. In Group 3, we have Federal Public Servants and State Public Servants, totaling 41,506 individuals. In Group 4, we have Accountants, Administrators, Company Directors, Bankers, Entrepreneurs, and Managers, totaling 177,940 individuals. In Group 5, we have Doctors, Economists, and Lawyers, totaling 58,286 individuals. Lastly, Group 6 consists Retirees, totaling 45,493 individuals. The total number of individuals in these six groups is 439,266. Panel A computes each subgroup's trading activity as the fraction of active investors from that subgroup over the total number of active retail investors each day. Panel B uses trading volumes instead. *Crypto-salience* is the first principal component computed from three variables: (i) the frequency of mentions of the words "Bitcoin" or "BTC" across Subreddit forums, (ii) the daily return of Bitcoin, (iii) the abnormal trading intensity in the major Bitcoin trading platforms. We include the same controls as in Table 2. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Fraction of retail investors (number)						
Crypto-salience	-0.079***	-0.026***	-0.027***	0.092***	0.053***	0.164***
	(-3.21)	(-4.38)	(-3.09)	(3.35)	(4.45)	(5.26)
Market returns	0.004	-0.001	-0.005	0.009	-0.023***	0.002
	(0.31)	(-0.56)	(-1.39)	(1.00)	(-5.44)	(0.32)
Market volume	-0.002	0.002***	-0.001**	-0.003***	0.003***	-0.003***
	(-1.38)	(5.96)	(-2.20)	(-3.06)	(3.83)	(-3.30)
Market volatility	0.031	-0.024***	0.023	0.278***	-0.061***	-0.065*
	(0.58)	(-3.13)	(1.63)	(6.31)	(-2.98)	(-1.75)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.36	0.85	0.72	0.43	0.41	0.91
Observations	1604	1604	1604	1604	1604	1604
Panel B: Fraction of retail investors (volume)						
Crypto-salience	-0.147***	-0.005	-0.081***	0.144*	-0.049**	0.163***
	(-3.77)	(-0.60)	(-3.94)	(1.86)	(-2.28)	(3.94)
Market returns	0.025**	0.004	0.015***	-0.021	0.001	0.025**
	(2.07)	(0.93)	(2.74)	(-0.75)	(0.13)	(2.08)
Market volume	0.001	-0.001***	-0.005***	0.022***	0.003**	0.003**
	(0.81)	(-3.00)	(-5.88)	(4.88)	(2.07)	(2.23)
Market volatility	-0.113*	-0.017	0.113***	-0.234*	-0.021	-0.202***
	(-1.84)	(-0.81)	(3.98)	(-1.66)	(-0.47)	(-3.33)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.56	0.07	0.53	0.24	0.15	0.28
Observations	1604	1604	1604	1604	1604	1604

Table 6: Crypto-salience and retail equity trading

The table displays regressions of daily retail equity trading activity on a daily proxy for crypto salience and control variables. *log(number)* is the log of the total number of retail investors active (buying or selling) in the equity markets on a given day. *log(volume)* is the log of the total volume traded (buying or selling) by retail investors millions of US dollars. *fraction* is the total volume traded (buying or selling) by retail investors divided by the total volume in the equity markets. In Panel A we consider only buying, in Panel B only selling, and in Panel C consider buying minus selling. *Crypto-salience* is the first principal component computed from three variables: (i) the frequency of mentions of the words "Bitcoin" or "BTC" across Subreddit forums, (ii) the daily return of Bitcoin, (iii) the abnormal trading intensity in the major Bitcoin trading platforms. As controls, we include: *Market return*, the cumulative returns of the Ibovespa over the past five trading days; *Market volatility*, the 5-day average of the daily range variation of the Ibovespa index; *Market volume*, log of the daily total volume in millions of US dollars; and a number of calendar controls: (i) day-of-the-week dummies, (ii) month dummies, and (iii) a time trend. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	log(number)		log(volume)		fraction	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: buying activity						
Crypto-salience	-0.081***	-0.072***	-0.069***	-0.055***	-0.727***	-0.718***
	(-4.71)	(-5.15)	(-4.09)	(-4.76)	(-5.04)	(-5.03)
Market returns		0.004		0.008***		0.132***
		(1.50)		(3.47)		(3.62)
Market volume		0.452***		0.680***		
		(16.14)		(24.35)		
Market volatility		-0.051***		-0.041***		-0.852***
		(-3.52)		(-3.29)		(-5.02)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.51	0.66	0.39	0.73	0.22	0.25
Observations	1727	1727	1727	1727	1727	1727
Panel B: selling activity						
Crypto-salience	-0.082***	-0.069***	-0.067***	-0.051***	-0.717***	-0.703***
	(-4.83)	(-5.59)	(-4.29)	(-5.28)	(-5.30)	(-5.43)
Market returns		0.026***		0.013***		0.196***
		(8.15)		(5.43)		(5.72)
Market volume		0.551***		0.747***		
		(18.75)		(25.46)		
Market volatility		-0.103***		-0.055***		-1.048***
		(-5.95)		(-4.40)		(-5.98)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.34	0.61	0.32	0.72	0.19	0.25
Observations	1727	1727	1727	1727	1727	1727

continuous next page...

... continuous from previous page

	log(Number)		log(Volume)		Fraction	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: buying minus selling activity						
Crypto-salience	0.001	-0.003	-0.002	-0.003	-0.010	-0.016
	(0.22)	(-0.50)	(-0.42)	(-0.84)	(-0.17)	(-0.29)
Market returns		-0.021***		-0.005***		-0.064***
		(-10.50)		(-3.58)		(-3.23)
Market volume		-0.099***		-0.066***		
		(-5.08)		(-4.98)		
Market volatility		0.052***		0.014**		0.196**
		(4.90)		(2.35)		(2.08)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.07	0.19	0.02	0.05	0.02	0.03
Observations	1727	1727	1727	1727	1727	1727

Table 7: Measures of crypto salience and retail equity trading

The table presents regressions of daily retail equity trading activity on various measures of crypto salience and control variables. $BitcoinReddit_t$ refers to the frequency of mentions of the words "Bitcoin" or "BTC" across the following Subreddit forums: Bitcoin, BitcoinBeginners, and BitcoinMarkets, divided by 100. $BitcoinReturn_t$ is the daily return, in percentage points, of Bitcoin calculated using the median price across the major Bitcoin trading platforms. $BitcoinTrading_t$ is the daily number of deals closed in the major bitcoin trading platforms, divided by the average of the same variable over the past year (i.e. from day t-252 to day t-1). In Panel A, retail equity trading activity is the log of the total number of retail investors active (i.e., buying and/or selling) in the equity markets on a given day. In Panel B, the log of total volume traded by retail investors (volume purchased plus volume sold) millions of US dollars. In Panel C, the total volume traded by retail investors divided by two times the total volume in the equity markets. As controls, we include: *Market return*, the cumulative returns of the Ibovespa over the past five trading days; *Market volatility*, the 5-day average of the daily range variation of the Ibovespa index; *Market volume*, the log of the daily total volume in millions of US dollars; and a number of calendar controls: (i) day-of-the-week dummies, (ii) month dummies, and (iii) a time trend. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	(1)	(2)	(3)	(4)
Panel A: log(number of retail investors)				
Bitcoin in social media	-0.006***			-0.005***
	(-5.09)			(-4.29)
Bitcoin return		0.001		0.001
		(0.46)		(0.43)
Bitcoin trading			-0.051***	-0.037***
			(-4.24)	(-2.98)
Market returns	0.014***	0.015***	0.015***	0.014***
	(4.80)	(4.98)	(5.19)	(5.08)
Market volume	0.524***	0.528***	0.511***	0.513***
	(18.60)	(17.77)	(17.95)	(18.50)
Market volatility	-0.092***	-0.075***	-0.060***	-0.077***
	(-5.76)	(-4.45)	(-3.90)	(-4.89)
Calendar controls	yes	yes	yes	yes
Adjusted R-squared	0.67	0.64	0.67	0.69
Observations	1728	1727	1727	1727

continuous next page...

... continuous from previous page

	(1)	(2)	(3)	(4)
Panel B: log(volume by retail investors)				
Bitcoin in social media	-0.004***			-0.003***
	(-3.83)			(-2.88)
Bitcoin return		-0.001		-0.000
		(-0.46)		(-0.21)
Bitcoin trading			-0.041***	-0.033***
			(-4.23)	(-3.24)
Market returns	0.011***	0.012***	0.012***	0.011***
	(4.52)	(4.70)	(4.89)	(4.72)
Market volume	0.726***	0.728***	0.715***	0.716***
	(25.41)	(24.92)	(25.29)	(25.47)
Market volatility	-0.059***	-0.047***	-0.035***	-0.045***
	(-4.55)	(-3.52)	(-2.77)	(-3.52)
Calendar controls	yes	yes	yes	yes
Adjusted R-squared	0.74	0.73	0.74	0.75
Observations	1728	1727	1727	1727
Panel C: fraction by retail investors				
Bitcoin in social media	-0.067***			-0.048***
	(-4.13)			(-3.24)
Bitcoin return		-0.004		-0.001
		(-0.27)		(-0.06)
Bitcoin trading			-0.585***	-0.443***
			(-4.09)	(-2.96)
Market returns	0.169***	0.182***	0.177***	0.169***
	(4.76)	(4.93)	(5.11)	(4.95)
Market volume	-3.264***	-3.228***	-3.422***	-3.403***
	(-10.75)	(-10.22)	(-11.27)	(-11.40)
Market volatility	-0.929***	-0.751***	-0.577***	-0.750***
	(-4.99)	(-3.87)	(-3.17)	(-4.02)
Calendar controls	yes	yes	yes	yes
Adjusted R-squared	0.36	0.31	0.36	0.38
Observations	1728	1727	1727	1727

Table 8: Crypto-salience and US retail equity trading

The table displays regressions of daily retail equity trading activity on a daily proxy for crypto salience and control variables. We follow (Boehmer, Jones, Zhang, and Zhang, 2021b) to identify marketable retail purchases and sales using publicly available U.S. equity transactions data. *Volume* is the log of the total volume traded by retail investors (volume purchased plus volume sold) millions of US dollars. *Fraction* is the total volume traded by retail investors divided by two times the total volume. *Crypto-salience* is the first principal component computed from three variables: (i) the frequency of mentions of the words "Bitcoin" or "BTC" across Subreddit forums, (ii) the daily return of Bitcoin, (iii) the abnormal trading intensity in the major Bitcoin trading platforms. As controls, we include: *Market return*, the cumulative returns of the SP500 index over the past five trading days; *Market volatility*, the 5-day average of the daily range variation of the SP500 index; *Market volume*, log of the daily total volume in millions of US dollars; and a number of calendar controls: (i) day-of-the-week dummies, (ii) month dummies, and (iii) a time trend. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	log(volume)		fraction	
	(1)	(2)	(3)	(4)
Crypto-salience	0.008	-0.017***	-0.216***	-0.186***
	(1.31)	(-3.75)	(-3.92)	(-3.79)
Market returns		0.007***		0.071***
		(3.47)		(3.31)
Market volume		0.884***		-1.192***
		(32.34)		(-3.49)
Market volatility		-0.012		-0.142
		(-1.15)		(-1.25)
Calendar controls	yes	yes	yes	yes
Adjusted R-squared	0.29	0.83	0.14	0.20
Observations	1445	1445	1445	1445

Table 9: Stock-salience and retail equity trading

The table displays regressions of daily retail equity trading activity on a measure of stock salience and control variables. *Stock-salience* is the frequency of mentions of the words "stock" or "stocks" in the major Subreddit forum used by retail investors, namely, Wallstreetbets. *Number* is the total number of retail investors active (i.e., buying and/or selling) in the equity markets on a given day, divided by 100. *Volume* is the total volume traded by retail investors (volume purchased plus volume sold) millions of US dollars. *Fraction* is the total volume traded by retail investors divided by two times the total volume in the equity markets. As controls, we include: *Market return*, the cumulative returns of the Ibovespa over the past five trading days; *Market volatility*, the 5-day average of the daily range variation of the Ibovespa index; *Market volume*, log of the daily total volume in millions of US dollars; and a number of calendar controls: (i) day-of-the-week dummies, (ii) month dummies, and (iii) a time trend. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	log(number)		log(volume)		fraction	
	(1)	(2)	(3)	(4)	(5)	(6)
Stocks in social media	2.045***	1.449***	2.103***	1.197***	9.893***	10.159***
	(9.25)	(8.11)	(9.94)	(8.88)	(5.72)	(6.44)
Market returns		0.016***		0.012***		0.181***
		(5.72)		(5.48)		(5.28)
Market volume		0.441***		0.657***		
		(16.17)		(23.72)		
Market volatility		-0.073***		-0.045***		-0.948***
		(-5.12)		(-3.87)		(-5.64)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.54	0.71	0.47	0.77	0.20	0.26
Observations	1728	1728	1728	1728	1728	1728

Table 10: Crypto-salience and retail equity trading (only those already active in 2012)

The table presents regressions of daily retail equity trading activity for individuals who were already active in the stock market during the first six months of 2012. The regressions include a daily proxy for crypto salience and control variables. *Number* is the total number of retail investors active (i.e., buying and/or selling) in the equity markets on a given day, divided by 100. *Volume* is the total volume traded by retail investors (volume purchased plus volume sold) millions of US dollars. *Fraction* is the total volume traded by retail investors divided by two times the total volume in the equity markets. *Crypto-salience* is the first principal component computed from three variables: (i) the frequency of mentions of the words "Bitcoin" or "BTC" across Subreddit forums, (ii) the daily return of Bitcoin, (iii) the abnormal trading intensity in the major Bitcoin trading platforms. As controls, we include: *Market return*, the cumulative returns of the Ibovespa over the past five trading days; *Market volatility*, the 5-day average of the daily range variation of the Ibovespa index; *Market volume*, log of the daily total volume in millions of US dollars; and a number of calendar controls: (i) day-of-the-week dummies, (ii) month dummies, and (iii) a time trend. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	log(number)		log(volume)		fraction	
	(1)	(2)	(3)	(4)	(5)	(6)
Crypto-salience	-0.047***	-0.042***	-0.041***	-0.032***	-0.373***	-0.373***
	(-3.64)	(-4.41)	(-2.74)	(-3.50)	(-3.93)	(-4.04)
Market returns		0.011***		0.010***		0.097***
		(4.81)		(4.15)		(3.83)
Market volume		0.475***		0.745***		
		(20.49)		(26.38)		
Market volatility		-0.057***		-0.042***		-0.542***
		(-4.58)		(-3.35)		(-4.23)
Calendar controls	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.25	0.60	0.09	0.65	0.37	0.40
Observations	1604	1604	1604	1604	1604	1604

Table 11: Crypto-salience and retail equity trading in 2012-2022

The table displays regressions of daily retail equity trading activity on a daily proxy for crypto salience and control variables using an extended dataset that contains aggregate information about retail trading from 2012 to 2022. *Volume* is the total volume traded by retail investors (volume purchased plus volume sold) millions of US dollars. *Fraction* is the total volume traded by retail investors divided by two times the total volume in the equity markets. *Crypto-salience* is the first principal component computed from three variables: (i) the frequency of mentions of the words "Bitcoin" or "BTC" across Subreddit forums, (ii) the daily return of Bitcoin, (iii) the abnormal trading intensity in the major Bitcoin trading platforms. As controls, we include: *Market return*, the cumulative returns of the Ibovespa over the past five trading days; *Market volatility*, the 5-day average of the daily range variation of the Ibovespa index; *Market volume*, log of the daily total volume in millions of US dollars; and a number of calendar controls: (i) day-of-the-week dummies, (ii) month dummies, and (iii) a time trend. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	log(volume)		fraction	
	(1)	(2)	(3)	(4)
Crypto-salience	-0.025*	-0.025***	-0.383***	-0.344***
	(-1.77)	(-3.56)	(-4.05)	(-3.66)
Market returns		0.013***		0.241***
		(4.93)		(5.85)
Market volume		0.886***		-0.629*
		(35.11)		(-1.76)
Market volatility		0.007		0.044
		(0.83)		(0.33)
Calendar controls	yes	yes	yes	yes
Adjusted R-squared	0.73	0.91	0.23	0.27
Observations	2721	2721	2721	2721

Table 12: Crypto-salience and retail equity trading in 2012-2022: Rolling window regressions

The table displays regressions of daily retail equity trading activity on a daily proxy for crypto salience and control variables using an extended dataset that contains aggregate information about retail trading from 2012 to 2022 across two-year rolling window samples. In Panel A, log of the total volume traded by retail investors (volume purchased plus volume sold) millions of US dollars. In Panel B, the total volume traded by retail investors divided by two times the total volume in the equity markets. *Crypto-salience* is the first principal component computed from three variables: (i) the frequency of mentions of the words "Bitcoin" or "BTC" across Subreddit forums, (ii) the daily return of Bitcoin, (iii) the abnormal trading intensity in the major Bitcoin trading platforms. As controls, we include: *Market return*, the cumulative returns of the Ibovespa over the past five trading days; *Market volatility*, the 5-day average of the daily range variation of the Ibovespa index; *Market volume*, log of the daily total volume in millions of US dollars; and a number of calendar controls: (i) day-of-the-week dummies, (ii) month dummies, and (iii) a time trend. Newey-West variance estimator with five lags to compute standard-errors are used. t-statistics are presented in parentheses. *, **, and *** indicate significance levels of 0.10, 0.05, and 0.01, respectively.

	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021	2021-2022
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: volume by retail investors										
Crypto-salience	-0.020***	-0.009	-0.004	-0.092***	-0.007	-0.034***	-0.030**	0.007	0.031***	0.119***
	(-3.04)	(-1.01)	(-0.43)	(-4.54)	(-0.53)	(-3.87)	(-2.27)	(0.32)	(2.67)	(6.94)
Market returns	0.007	0.004	0.007***	0.016***	0.010***	0.007*	0.008***	0.014***	0.017***	0.011***
	(1.58)	(1.28)	(2.65)	(4.55)	(3.11)	(1.76)	(2.66)	(6.02)	(5.31)	(2.89)
Market volume	0.436***	0.550***	0.505***	0.576***	0.601***	0.758***	0.793***	1.157***	0.688***	0.806***
	(10.05)	(11.31)	(10.10)	(11.35)	(13.03)	(25.45)	(20.83)	(30.06)	(12.62)	(16.74)
Market volatility	0.036*	0.032*	0.017	-0.022	-0.060***	0.035**	-0.050***	0.017**	0.012*	-0.033
	(1.82)	(1.79)	(0.96)	(-0.75)	(-3.00)	(2.01)	(-3.43)	(2.23)	(1.96)	(-1.49)
Calendar controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.57	0.60	0.62	0.58	0.71	0.78	0.76	0.85	0.57	0.73
Observations	493	496	494	495	495	491	493	497	496	497
Panel B: fraction of volume by retail investors										
Crypto-salience	-0.339***	-0.098	-0.042	-1.376***	-0.131	-0.543***	-0.482**	0.112	0.553**	1.968***
	(-4.50)	(-1.05)	(-0.44)	(-4.67)	(-0.73)	(-3.95)	(-2.07)	(0.25)	(2.34)	(6.96)
Market returns	0.122**	0.104***	0.155***	0.243***	0.187***	0.117**	0.146***	0.271***	0.301***	0.139**
	(2.11)	(2.64)	(4.85)	(4.49)	(3.62)	(2.00)	(3.19)	(5.47)	(4.50)	(2.05)
Market volume	-6.043***	-4.211***	-4.564***	-4.534***	-5.352***	-3.972***	-3.574***	3.227***	-6.346***	-2.834***
	(-14.70)	(-12.00)	(-13.58)	(-7.45)	(-10.73)	(-9.36)	(-5.70)	(4.11)	(-5.38)	(-3.75)
Market volatility	0.534*	0.153	0.047	-0.483	-0.887***	0.456*	-0.926***	0.301*	0.149	-0.840**
	(1.84)	(0.70)	(0.20)	(-1.18)	(-2.98)	(1.70)	(-4.13)	(1.87)	(1.16)	(-2.15)
Calendar controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adjusted R-squared	0.56	0.41	0.53	0.35	0.49	0.39	0.34	0.34	0.36	0.44
Observations	493	496	494	495	495	491	493	497	496	497