Celebrity Persuasion*

Matteo Benetton, *UC Berkeley*
William Mullins, *UC San Diego*
Marina Niessner, *Indiana University*
Jan Toczynski, *QMUL*

November 2024 - preliminary

Abstract

Celebrities have long leveraged their influence to shape outcomes in politics, marketing, and now in cryptocurrency markets. As investors increasingly rely more on social media for financial news and investment guidance, celebrities are playing a larger role in the financial advice landscape. Using survey, market, and transaction-level data, we examine the persuasion rates of celebrity cryptocurrency endorsements on Twitter. Investors appear to treat these celebrity tweets as financial advice: controlling for crypto-related news, the probability of cryptocurrency investment by individuals on tweet days increases by 13.5%, with stronger effects among men, wealthier individuals, and older investors. We find that celebrities have high persuasion rates, ranging from 9% to 13%, and they impact equilibrium outcomes – market trading volume in the targeted coin increases by 7% in the hour following the celebrity tweet. Finally, we show that a representative retail investor who trades following celebrity tweets makes negative returns after transaction costs.

Keywords: Persuasion, Social media, Retail trading, Social finance, Financial advice

JEL Codes: E31,E42,G11,G23,G51

This is not Financial Advice. Matteo Benetton (benetton@berkeley.edu); William Mullins (wmullins@ucsd.edu); Marina Niessner (mniessne@iu.edu); Jan Toczynski (j.toczynski@qmul.ac.uk). We thank Matt Billett, Tony Cookson, Diego Garcia, Isaac Hacamo, Mattia Landoni, Charles Martineau, and Terry Odean for helpful suggestions. We also thank participants at Indiana University, UC Berkeley, the USC Social and Behavioral Finance Conference, Chapman University, UW Foster, Boulder Summer Conference on Consumer Financial Decision Making, FutFinInfo and Universidad de los Andes for many helpful comments. All remaining errors are our own.

1. Introduction

Celebrities have been used to persuade consumers to buy products for over two hundred years (NPR, 2012). More recently, the reach and immediacy of social media have led to a growing use of celebrity-influencer marketing (IMH (2023), New York Times (2021)). As younger adults increasingly use and trust social media as a source of news (Pew Research, 2022), real-world celebrities—including Hollywood actors, musicians, and sports stars—have begun to endorse financial products related to the largely unregulated cryptocurrency sector, with ambiguous impacts on investors (Bloomberg, 2022). For example, Kim Kardashian paid a large fine to the SEC in late 2022 after promoting cryptocurrency Ethereum Max (EMAX)[1] to her then 250 million Instagram followers — *"This is not financial advice but just sharing what my friends just told me"* — without disclosing that she had been paid to do so (CNBC, 2022). In this paper, building on a large literature on persuasion (e.g., DellaVigna and Gentzkow (2010), Hu and Ma (2021)), we estimate the persuasion rates of celebrity crypto endorsements on Twitter on individuals' investment decisions and explore the characteristics of people who subsequently invest. We also examine the effects of celebrity endorsements on crypto markets more broadly.

We focus on the ecosystem of celebrity crypto endorsements for three reasons. First, while celebrity endorsements are used in many settings, including politics, measuring the persuasion rates of political endorsements can be tricky as we demonstrate in Figure 1. When Taylor Swift endorsed Harris on September 10, 2024, the number of donations overall and from first-time donors soared (subfigures (a) and (c)). However, the persuasion rate of her message is hard to estimate, as it came on the heels of the debate. While any celebrity persuasion attempts are endogenous, focusing on the crypto setting allows us to examine a multitude of events where we can have very precise controls for outside influences and high-frequency measured outcomes.

Second, most of the existing literature on financial advice has focused on certified financial advisors providing guidance on stock markets, since a large fraction of individual investors turn to these professionals for equity investment guidance.[2] While cryptocurrency

[1] EMAX has no connection to Ethereum, which is a popular and well-established cryptocurrency.
[2] https://www.riaintel.com/article/2buzyinjbu0qt7sc9xxc0/practice-management/are-social-media-

markets have grown rapidly over the past decade—more than 1-in-10 Americans own cryptocurrencies (Weber et al., 2023), while in France more people own cryptocurrencies than stocks (Bloomberg, 2023)—due to skepticism or lack of expertise in this new asset class, certified professional advisors have a substantially smaller role in the crypto sector.[3] The combination of a relative lack of *supply* of advice by professionals and an increasing *demand* for advice by retail investors has opened the door to new participants: real-world celebrities - like Kim Kardashian - who have millions of followers on social media and little or no knowledge about the financial products they endorse.

We use several data sources to study the persuasiveness and market-wide implications of celebrity financial advice. We begin by using Morning Consult microdata from a survey conducted around the time of the Kim Kardashian SEC enforcement action. Despite Kardashian's clear lack of financial expertise, the survey suggests that many followers took her advice: almost 20% of survey respondents who had seen her post said that they invested in EMAX. This translates to a persuasion rate of at least 13%, which is large compared to persuasion rates commonly found in the literature (DellaVigna and Gentzkow, 2010). To further explore the quantitative importance of celebrities' financial social media posts and the types of investors who act on them, we utilize all tweets about major cryptocurrencies by top 52 real-world celebrities turned crypto influencers, together with transaction-level data gathered by a U.S. fintech company, Albert.[4] We find that after controlling for crypto-related news, celebrity tweets are associated with a 13.5% increase in the probability of investing in crypto, driven by men, higher income users, and users with excellent credit scores. This effect translates into a persuasion rate of about 10%, thus showing that celebrity messages can have wide-reaching implications for retail investors. Moving to market-level data, we then use hourly price and volume data for the seven major cryptocurrencies in our sample to show that returns and trading volume increase in the hours leading up to the celebrity tweets and stay elevated for several days after. Using trade-level data for Dogecoin, we find that these increases are driven by large trades – those over $1,000. Finally, we examine how

influencers-out-influencing-financial-advisors

[3]A 2021 NORC survey found that 24% of crypto investors get their financial advice from social media, whereas only 2% listen to brokers and financial advisors (Woelfel, 2021).

[4]The coins in our tweet-based sample are Bitcoin (BTC), Ether (ETH), Doge (DOGE), Ripple (XRP), Cardano (ADA), Polygon (MATIC), and Shiba Inu (SHIB).

investors would have performed if they had bought into the cryptocurrency before vs. after the celebrity tweets. While investors buying *ahead* of the tweet would have performed well, investors buying *after* the tweet likely made negative returns after accounting for transaction costs and would have been better off buying Bitcoin (or Ethereum) rather than the focal coin of the tweet.

We now describe our findings in greater detail. First, we use survey micro-data to shed light on the extent to which people follow celebrity financial advice and the characteristics of those who do so. We use a nationally-representative survey conducted by Morning Consult around the SEC's enforcement action against Kim Kardashian. This survey included detailed questions about individuals' investments, demographic characteristics, opinions about celebrity influencers, and social media usage. Respondents who invest in crypto are more likely to be male, younger, Black or Hispanic, self-employed, have a higher income and education, and live in urban areas. Respondents who had *seen* her post were also more likely to be male, younger, Black or Hispanic, wealthier and urban relative to those who had not seen the post. Furthermore, according to the survey, almost 20% of respondents who saw her post ended up investing in EMAX, a strikingly high response rate to a celebrity social media post, especially given that 18% of respondents said they had seen her post. Focusing only on investors who saw her post, we find that those who subsequently invested were more likely to be male, young, and live in urban areas, but there were no statistically significant differences by race or education. In sum, the evidence from the survey indicates i) that young, male, urban-dwellers from under-represented minorities are more likely to invest in cryptocurrencies, and ii) they are also more likely to see celebrity social media posts and act upon them. Using the framework from DellaVigna and Gentzkow (2010), we compute a lower bound on the persuasion rate of about 13%.

Next, we use transaction-level data from Albert, an account aggregator Fintech firm, to dig deeper into the question of who invests in cryptocurrencies and follows the investment advice of real-world celebrities. Instead of focusing on the Kardashian post, we examine crypto-related tweets by 52 celebrities. Albert's main service is to aggregate checking and credit card accounts in one place, to provide money management tips, and to help users set saving goals. Our data contains the transactions of over 80,000 active users on Albert between June 2020 and February 2023. While we cannot observe which cryptocurrencies individuals invest in, we do observe when investors move money in or out of all major crypto platforms and exchanges, similar to Aiello et al. (2023) – we term these "crypto investments." Using an event-study design, and controlling for crypto-related news using data from Factiva and StockTwits,[5] we find that on days with celebrity tweets the probability of investing in crypto increases by 13.5% relative to the baseline investment rate in the week prior. This increase in investment probability occurs on the day of the tweet and returns to baseline after several trading days. Moreover, the effect appears relatively homogeneous across tweets about different cryptocurrencies, except for DOGE, where celebrity tweets garner a larger reaction. Overall, the analysis of transactions microdata shows that a subset of investors quickly respond to celebrity tweets by shifting funds into their crypto investment accounts. We assume that about 3% of investors in the US have been exposed to the message, and estimate a persuasion rate of about 9.2%. Of course, like with any message aiming at persuading people, the timing of tweets themselves is not exogenous, as can be seen in Figure 2 where we plot the number of tweets at the monthly level along with the price of Bitcoin. However, most investors, especially retail investors on Albert, are not aware of the upcoming tweet. Therefore, by focusing on the reaction to the tweet, and by controlling for other contemporaneous cryptocurrency news and cryptocurrency prices, we isolate the response of retail investors to the celebrity tweets.

We then explore the characteristics of Albert investors that act on celebrity tweets. Men, wealthier users, users over 35, and users with 'excellent' credit score are more likely to react to celebrity endorsements. We further test whether certain types of celebrities are more effective in moving their followers to action, but find a largely homogeneous effect across celebrity classes (e.g., sports stars vs. actors), although musicians appear to have a stronger effect and celebrities from Shark Tank have a weaker effect. Importantly, we also show that our results are not driven by any individual celebrity, such as Elon Musk. Lastly, we use investors' zipcodes to estimate whether individuals' political affiliation or race affects susceptibility to celebrity tweets. Investors from zip codes with a higher Black population

[5]While we only control for attention to cryptocurrencies using one social media platform – StockTwits – as Cookson et al. (2024) shows, attention is strongly correlated across the major social media platforms.

share are less likely to invest following tweets, while those from zip codes with a high Asian share are more likely. We do not find a significant difference by political affiliation.

While the evidence thus far shows that individuals respond to celebrity influencers' tweets as if it were financial advice, it remains unclear whether these endorsements have any impact on crypto markets more broadly. To examine this, we use our sample of celebrity tweets and hourly price and trading volume data. In an event-study design that controls for crypto-related news using data from Factiva and StockTwits, we find that returns begin to increase at an accelerated rate around a day prior to a celebrity tweet, and continue to increase for at least 12 hours following the tweet. Furthermore, we show that a tweet is associated with a 7% increase in trading volume in the hour following the tweet, and remains elevated for several days.

To decompose the increase in trading volume around celebrity tweets, we then use trade-level data for Dogecoin to examine the evolution of trade sizes around the tweet. The average trade size increases in the days leading up to the tweet and stays elevated in the days following the tweet; in the hour of the tweet there is a 6% spike in the size of the trades. Breaking trades down into size bins, we find that the dollar share of trades below $1,000 clearly decreases in the day leading up to the tweets, while the share of trades above $1,000 and especially above $10,000 sharply increases. The dollar share of larger trades stays elevated in the days following the tweets. This suggests that either individual investors increase their trade sizes around the tweets, or that larger traders move into the Dogecoin market around the time of the tweets. While Elon Musk makes up a third of tweets about Dogecoin, we find that these results become stronger when we exclude his tweets.

In the final part of the paper we examine how individual investors would have performed if they invested after seeing the tweet. Individuals trading in the hours leading up to the tweets either bought the coins by chance, or have prior knowledge of an upcoming tweet; retail investors are more likely to be buying the coins *after* the tweets. While we do not observe exactly when retail investors purchase the coins, it is probably safe to assume that they were not privy to the information about the upcoming tweet. Therefore, we examine how investors would have performed had they bought the coins in the hours following the tweets, and compare that to the performance of purchases in the hours before the tweet. We find that investors who bought before the tweets and sold after would have had an average performance of 2.8% whereas investors who bought after and sold after the tweets would have only made 0.4%. Given an average trading fee of about 50bps in popular trading platform (e.g., Coinbase), a representative retail investor trading following celebrity tweets would have made negative returns after accounting for transaction costs. Finally, we compare the gross returns to how they would have done had they bought Bitcoin instead of the tweeted-about coin (or Ethereum if the tweet was about Bitcoin). We label the difference as the abnormal return, and find that investors who bought the coin after the tweet had an abnormal return of -0.5%, suggesting that they would have been better off buying BTC or ETH than the coin mentioned in the tweet.

Related literature. Our paper makes several contributions to the existing literature. There is a large literature that explores the incentives of financial advisors (e.g.,Célérier and Vallée (2019), Egan (2019), Pool et al. (2016)), and finds that the financial advisors who get caught misbehaving often face few repercussions (e.g., Egan et al. (2019), Egan et al. (2022)). Additionally, prior research has examined the effect of celebrities' advice for non-financial products on adoption of the products (e.g, Erdogan (1999), Tzoumaka et al. (2016)). However, there is little research into the effects and quality of advice that investors receive from real-world celebrities, who have no expertise in the subject they promote, are not consistently covered under consumer protection laws, and often don't disclose conflicts of interest. We contribute to filling this gap by studying the impact of the advice of real-word celebrities about cryptocurrencies and by examining the demographics of the investors who follow this advice. By interpreting our results through the lens of a persuasion framework, we provide novel empirical evidence on celebrities persuasion rates for individual investment decisions.[6] Hence our work is related to the large literature on persuasion and more specifically to the literature on persuasion in finance (Mullainathan and Shleifer, 2005, Reuter and Zitzewitz, 2006, Mullainathan et al., 2008, Hu and Ma, 2021, Iyer and Manso, 2023).

Our results also contribute to the growing literature that studies individuals that invest in cryptocurrencies. Aiello et al. (2023) and Pursiainen and Toczynski (2022) find using

[6] DellaVigna and Gentzkow (2010) provide a general discussion on persuasion rates and a review of results from different studies and settings.

consumer transaction data that crypto investors tend to younger, more male, wealthier, slightly more white, and more educated. Similarly, Weber et al. (2023) user survey data and find that crypto holders tend to be younger, whiter, more male and libertarian relative to non-crypto holds. We find a similar pattern in our survey data, and contribute to the existing literature by examining the characteristics of investors that tend to not just buy cryptocurrencies, but do so based on advice from real-world celebrities.

We also contribute to the literature on financial advice on social media. For equity markets, recent research documents that there is information in social media signals (e.g., Chen et al. (2014); Farrell et al. (2022); Cookson et al. (2024)). By contrast, Kakhbod et al. (2023) finds that, while there are some skilled investors who post on social media platforms, the majority are either unskilled or negatively skilled. In the crypto space Li et al. (2021) examine pump-and-dump schemes on apps like Telegram and find that investors who trade in advance realize large returns, while 'outsiders' who trade during later stages can lose large amounts of money. Merkley et al. (2023) study the advice of 180 most prominent crypto-influencers on Twitter, and find that they are followed by positive short-term and negative long-term returns. They find this effect is especially strong for influencers who claim to be professional financial analysts, which make up the majority of their sample. Our paper differs in that we focus on real-world celebrities, who clearly have no financial expertise and have followings that are often orders of magnitude larger. We are also able to observe the characteristics of investors who follow the advice of these celebrity finfluencers. White and Wilkoff (2023) examine the outcomes of celebrity endorsements of ICOs, and find that they increase the total funds raised and the likelihood of being listed on an exchange. In the closest part of their paper to ours is that they show that celebrity endorsements seem to not be associated with greater ex-post ICO success, but are instead more likely to be associated with ICO scams. ICOs are very different from the cryptocurrencies we examine in our paper: ICOs are the earliest stage in the cryptocurrency lifecycle, while we examine well-established coins that are widely traded on exchanges and have large total market capitalizations.

2. Data and summary statistics

2.1 Survey

We obtained survey data from Morning Consult, a business intelligence company that specializes in online survey research technology. The survey was conducted in September 2021, and covered 2,200 adults in the US to understand household views of celebrities and their impact on financial decisions. The focus of the survey was on the cryptocurrency industry and the June 14, 2021 post on Instagram by Kim Kardashian. We obtained access to the raw data at the respondent level. For each respondent we observe their responses to questions related to investments (e.g., if they invest in cryptocurrencies), their usage of social media, and their opinion about celebrity influencers (e.g., if they saw the post by Kim Kardashian and their opinion about her), as well as a large set of self-reported demographic characteristics (gender, age, ethnicity, income, education, employment status, and zipcode).

2.2 Celebrity Tweet data

We focus on Twitter over other social media platforms because of the unique role it plays in the crypto ecosystem: "To a certain extent, the discussion of the industry on Twitter isn't *about* the industry — it *is* the industry ... Twitter is (for now) indispensable to following blockchain technology" (Axios, 2022). We assembled our core dataset of tweets on cryptocurrencies posted by celebrities in several steps. First, we searched on Google for the terms "celebrity crypto" and noted the names of every celebrity mentioned in all the links on the first two pages of search results. We also searched for variants of these keywords such as "celebrity" or "celebrities" followed by the names of the top 20 coins on Coinmarketcap.com excluding stablecoins and exchanges. We supplemented this list with the names of celebrities named in the media as either investors in FTX or in lawsuits related to the collapse of the exchange. To focus our study on celebrities without crypto-specific expertise we omitted celebrities that are famous exclusively for their roles as online crypto or financial influencers and all celebrities directly involved in the management or founding of crypto products and related financial apps (e.g., Vitalik Buterin). Table A1 lists the 52 celebrities, the number of crypto-related tweets by each in our sample, the number of Twitter followers, their gender and race, and a classification into five categories: Celebrity (mostly movie stars and models), Musicians, Sports stars, Shark Tank cast members (Mark Cuban and Mr Wonderful), and finally Elon Musk in a category of his own. We provide some examples of celebrity tweets in the Appendix Figure A1. Figure 2 plots the number of tweets over time on the left y-axis and the Bitcoin price on the right y-axis. There is a strong relationship between the bitcoin price and the number of celebrity tweets, especially during 2019-2021 period.

We then collected every available tweet posted by the celebrities on our list, and ran all tweets through a regular expressions filter that identifies and keeps tweets with the terms mentioned in Table A2.[7] This regex filter excludes some relevant tweets and includes some tweets that are not in fact about crypto, or are critiques rather than positive mentions. Both types of cases will lead to attenuation of our estimates. Finally, we added any tweets explicitly mentioned in (i) the filings of the class action lawsuit against Elon Musk and others (New York Southern District Court, 2022) alleging manipulation of the price of Dogecoin, or (ii) Ante (2023) on Elon Musk. We then manually read through the remaining tweets and excluded those that are clearly not about cryptocurrencies. Our final dataset consists of tweets about seven coins: Bitcoin (BTC), Ether (ETH), Doge (DOGE), Ripple (XRP), Cardano (ADA), Polygon (MATIC), and Shiba Inu (SHIB).

Table 1 Panel A shows the number of tweets per coin. Bitcoin makes up 61% of the tweets, with Dogecoin making up 17% and Ethereum and Shiba Inu each making up another 7%. In Table 1 Panels B through D, we show summary statistics on the number of tweets by celebrity demographic characteristics. Overall only 1.91% of our tweets come from female celebrities, and the rest are from male. 59% of the tweets are from white celebrities, 40% from Black celebrities, and 2 tweets from Asian celebrities. Overall, Elon Musk makes up 9.33% of the tweets, with the rest being fairly equally distributed among the other categories, except for "Sports," which makes up 26.44% of the tweets. Note that the average tweet is written by a celebrity with 15 Million followers.

[7] Words 'ton', 'pot', 'nft', 'near', 'link', 'leo', 'etc', 'dot', 'cream', 'cob', 'atom', 'ape', 'crypto', 'blockchain', 'stellar', 'stacks', 'nft', 'avalanche', 'cosmos','crypto','tron', 'cryptocurrency', 'cryptocurrencies' are too common, and produce a lot of false positives. Therefore, we required that they are preceded by either a "#" or a "$".

2.3 Individual-level data from an aggregator app

To study the response of cryptocurrency investments at the retail investor level, we use detailed transaction-level data gathered by Albert, a financial aggregator application available in the U.S. The main service offered by the app is account aggregation: users link their bank and card accounts to the app, which then organizes information from multiple accounts in one place. In addition, Albert gives its users money management tips and provides services such as setting savings goals and cash advance payments.

Albert shared with us an anonymized dataset of transactions from linked accounts of over 80,000 active users covering the period from June 2020 to early February 2023. To be in the sample users are required to (i) have been on the app since at least early 2021, (ii) have linked their main checking account, and (iii) have logged on to the application in the last month of the sample.

For each transaction in the dataset we observe the amount, date, user and account identifiers, and a text field containing the name of the corresponding merchant. We use the merchant information to identify cryptocurrency investments and disinvestments in the data. For example, we search for keywords such as *Coinbase* or *crypto hub*.[8] Overall, we identify nearly 290,000 deposits and over 40,000 withdrawals associated with cryptocurrencies. While this strategy allows us to identify flows to and from cryptocurrency accounts, we do not observe actual trading activity within these accounts. For more details about the data, see Toczynski (2023) and Pursiainen and Toczynski (2022) who use an earlier version of the dataset.

Transaction information can be further linked to a rich set of user-level variables such as self-reported income, age, gender and zip code. Table 2 presents the summary statistics of main user-level variables.[9] Figure 3 compares the distribution of age and income in the sample (as well as those users that invest in crypto) with those of the U.S. population (as measured in the 2020 Current Population Survey). As is clear from the figure, the sample skews substantially younger than the U.S. population, with an average age of nearly

[8]Table A3 in the appendix includes the list of keywords we used to identify cryptocurrency transactions. Most identified transactions come with the title *Coinbase*.

[9]We also include a series of variables derived from the transaction data - see the table notes.

33. Income is more similar to the overall population, although slightly higher: median reported income stands at over $42,000. Interestingly, around 60% of users for whom we observe gender are female, reflecting the focus of the application on money management and budgeting rather than on investing.

The lower panel of Table 2 repeats the exercise with crypto investors – users for whom we observe at least one cryptocurrency transaction. We use only individuals that invest in cryptocurrencies in our regressions and they represent around 20% of the sample. These users are more likely to be male and have a higher income (for a comprehensive analysis of the demographics of crypto investors, see Pursiainen and Toczynski 2022). Figure 3 shows that they are similar to the full sample in terms of age, but have somewhat higher incomes.

Table 3 presents the summary statistics at the cryptocurrency investor and transaction levels in the upper and lower panels respectively. An *investment* refers to a flow to a cryptocurrency brokerage, while a *withdrawal* refers to a flow in the opposite direction. On average, the crypto investors in our sample deposited a cumulative total of $3,018 into their cryptocurrency accounts over the two-and-a-half-year time period. However, investments are concentrated within a small number of most active investors. An average crypto deposit is around $165 (with a median of $33). Withdrawals are, on average, substantially larger, with an average of nearly $600, but are relatively rare.

2.4 Crypto Hour-level Price and Trade data

For crypto hourly-level price and trading volume we obtain data from CoinAPI from exchanges: Binance, Bitstamp, Coinbase, Kraken, and Kucoin. We also obtain trade-level data from CoinAPI for all trades in Dogecoin on Binance.

2.5 Crypto News

To control for cryptocurrency news in the market, we obtain the number of tweets about BTC, ETH, DOGE, XRP, ADA, MATIC, or SHIB on StockTwits at the hourly level. We also collect from Factiva the number of stories about "Cryptocurrency Markets" (one of Factiva's subject categories), at the daily level.

3. Framework and Survey evidence

3.1 Framework

We borrow a simple framework from the literature on persuasion to interpret our results and provide a better sense of the quantitative role of celebrities in affecting investor behavior. A large portion of the literature on persuasion is concerned with measuring the effect of persuasive communications on behavior. Similarly, our paper is concerned with measuring the effect of celebrity (persuasive) communications on investors behavior.

Following the approach in DellaVigna and Kaplan (2007) and DellaVigna and Gentzkow (2010) we define a persuasion rate. In a setting with a binary outcome (e.g., investing in an asset vs. not) and a binary treatment (e.g., observing a celebrity post vs. not), the persuasion rate (f) is given by:

$$f = 100 \times \frac{y_T - y_C}{e_T - e_C}\frac{1}{1 - y_0} \tag{1}$$

where y_T (y_C) is the share of treated (control) individuals adopting the behavior of interest (e.g, investing in an asset), e_T (e_C) is the share of treated (control) individuals receiving the treatment, and y_0 is the share that would adopt the behavior of interest is there was not treatment.[10]

The advantage of using equation (1) over simple comparison of different treatment effects from our empirical estimates is threefold. First, equation (1) adjust for the fraction of individuals receiving the treatment (e.g., observing the post by celebriries). Second, using a standard persuasion rate metric from the literature facilitate a quantitative comparison of the effect of celebrity communications relative to other setting previously studied. Third, exploiting heterogeneity in persuasion rate across heterogeneous characteristics of senders (celebrities) and receivers (investors) we can relate our results to different predictions of existing models of persuasion (beliefs- vs. preference-based).

[10]Following DellaVigna and Gentzkow (2010) when y_0 is not observed we approximate if with y_C.

3.2 Survey Evidence

In this section we provide survey evidence on the characteristics of investors who follow celebrity influencers' financial advice. We first focus on a specific Instagram post by Kim Kardashian as an illustrative example and broaden our sample of celebrity influencers in the next sections. While our focus in this section limits the external validity of the results, the event we study represents what the UK Financial Conduct Authority defined as *"the financial promotion with the single biggest audience reach in history"*.[11] This refers to a June 14, 2021 post on Instagram by Kim Kardashian, who asked her over 250 million Instagram followers to join the Ethereum Max Community by posting the story shown below.

Kim Kardashian's post on Ethereum Max

Using data from a nationally representative survey with 2,200 respondents conducted by Morning Consult we explore the determinants of overall holdings of cryptocurrencies and dig deeper into the investment in Ethereum Max following the Kim Kardashian Instagram post in Table 4.

We begin by looking at the role of investor demographics. Column 1 of Table 4 shows the results of a linear probability model in which the dependent variable is an indicator equal to one if the respondent holds any cryptocurrencies. We find that crypto holdings are associated with being male, younger, Black or Hispanic, self-employed, having a higher

[11]See https://www.fca.org.uk/news/speeches/risks-token-regulation

income and education, and living in urban areas. These results are broadly in line with the results in the literature studying the characteristics of cryptocurrency holders with survey or app-level data (Hasso et al., 2019, Lammer et al., 2019, Chan et al., 2020, Bonaparte, 2021, Benetton and Compiani, 2023).

Next, we investigate which demographic characteristics are associated with a higher likelihood of having seen, read, or heard about the Kim Kardashian Instagram post on Ethereum Max. In column 2 of Table 4 we find that young males (below age 35) who live in urban areas and are self-employed are the most likely group to be aware of the post. Interestingly, both Hispanic and Black respondents are significantly more likely than White respondents to have heard about the post. We do not find significant patterns in terms of education, while respondents with income above one hundred thousand dollars are more likely to have seen the post. Overall, 18% of survey respondents have seen, read, or heard about the Kardashian Ethereum Max post, consistent with the huge audience reached by celebrity influencers.

Finally, in column 3 of Table 4 we focus on individuals who said that they heard about the Kim Kardashian post (the 18% of individuals from column 3). We estimate a linear probability model in which the dependent variable is an indicator equal to one if the respondent invested in Ethereum Max after seeing the Kardashian post. In column 3 we find that 19% of respondents who saw the post say they ended up investing in Ethereum Max. This level of conversion suggests that celebrity influencers can potentially have a large impact on household asset allocation.

To gauge the magnitude of the effect we compute the persuasion rate of this single post using equation (1). The advantage in this case is that we know: (i) the share of survey respondent that saw the post, which allow us to compute the precise exposure rate: $e_T - e_C = 18\%$; and (ii) the share of treated individuals investing as a result: $y_T = 19\%$. The only unobservable is the share of control individuals who would have investment in Ethereum Max if there was no post by Kim Kardashian (y_C). From the survey, we know that the unconditional fraction investing in any cryptocurrencies is 17%. Using this number as an estimate of y_C, we compute a lower bound on the persuasion rate of about 13%. This magnitude is larger than persuasion rates commonly found in the literature for direct product advertising to consumers and on the higher end of persuasion rates from direct political communication (e.g., targeted door-to-door campaigns) and news media.[12]

We furthermore find that the individuals who obtain Ethereum Max after seeing Ms. Kardashian's post have several characteristics in-common with general cryptocurrency holders in column 1. They are more likely to be male (even if the effect is only marginally significant), young, and live in urban areas. However, these individuals also differ from the general cryptocurrency holders along several dimensions. For example, while cryptocurrency holders tend to have higher education and income (see column 1), there is no clear pattern for respondents who invested in Ethereum Max after seeing the Instagram post by Kim Kardashian. Furthermore, the effect of race is insignificant in column 3.

We next examine whether individuals' likelihood of investing in cryptocurrencies and Ethereum Max depends on the opinions they hold about celebrities. In particular, we focus on whether individuals had a positive or negative opinion about Kim Kardashian and Elon Musk. We present the results in Table 5. All columns control for demographic characteristics, since we want to study the marginal effect of opinions about celebrity influencers on the whether they invest in cryptocurrencies and Ethereum Max. In column 1 we look at general crypto holdings. As a placebo, we show that positive or negative opinions about Kim Kardashian and Elon Musk (the two celebrities that the survey focused on) are not associated with differential overall holdings of cryptocurrencies. Column 2 shows that respondents with positive (negative) opinions about Kim Kardashian were more (less) likely to have seen the post. These results are consistent with fans being more likely to follow and to be more attentive influencers' posts.

In the last column we examine how different opinions about Kim Kardashian and Elon Musk affected the individuals' propensity to have bought Ethereum Max after seeing Kim Kardashian's post. In column 3 we find that respondents with positive (negative) opinions about Kim Kardashian are more (less) likely to follow her financial advice. Despite the limited sample size the effects are statistically significant and the magnitudes are large. Having a favorable (unfavorable) opinion about Kim Kardashian increases the likelihood of following her advice to invest in Ethereum Max by about 50% relative to the average investment probability after the post. If we interpret a positive opinion about Kim Kardashian as a

[12]See DellaVigna and Gentzkow (2010) for a comparison across different studies using persuasion rates.

measure of her credibility as a sender, the heterogeneity result is consistent with bayesian belief-update models, which predict that the rational response is larger when the sender is more credible. However, the result can also provide corroborative evidence that influencers' popularity spill over beyond their area of expertise (and credibility) and into retail investment choices, thus affecting investors' behavior without truly changing their beliefs.

As a placebo test, we show in columns 2 and 3 that having a positive or negative opinion of Elon Musk doesn't have an effect on the likelihood of having seen and followed Kim Kardashian's Ethereum Max advice. Table A4 in the Appendix explores heterogeneous effects across different demographics. We find that non-White, young respondents with low income and education and a non-standard job are more likely to invest in Ethereum Max following the Kardashian post, if they have a positive opinion about her.

4. Celebrities' Impact on Crypto Retail Investors

In this section, we analyze transaction-level data shared with us by a Fintech firm, Albert, to explore both the extent to which retail investors follow celebrity influencers' cryptocurrency-related tweets, and the characteristics of those who do. As described in Section 2, while we cannot observe which specific coin the investors put their money in, we can observe when they move money in or out of crypto-specific exchanges.

To perform the analysis, we first aggregate users' flows in and out of cryptocurrency accounts at the individual investor-day level (it). Since investment transactions from weekends and holidays are registered on the *next business day*, we restrict our sample to business days and assign any tweets occurring on weekends or holidays to the next working day. We treat each celebrity-day observation as an event, keeping a window spanning seven days before and after each tweet for each individual investor, and we stack each 15-day-long event for each individual investor into a dataset at the event$\times$day$\times$individual investor level.[13]

To analyze the impact of tweets on investment flows, we estimate the following event-

[13] If a celebrity has multiple tweets on day t, we treat this as one event.

study specification:

$$
\begin{aligned}
Outcome_{eti} = & \sum_{h=-7}^{7} \alpha_h EventDay_{e,t_0+h} \\
& + \Gamma_e + \Lambda_{dow(t)} + \Xi_i + \rho_t + \phi_{pre} \mathbb{1}_{et}^{Pre\ tweet} \\
& + \sum_{k=1}^{7} \delta_k Factiva_{e,t_0-k} + \sum_{k=1}^{7} \theta_k StockTwits_{e,t_0-k} + \epsilon_{eti},
\end{aligned} \tag{2}
$$

where $Outcome_{eti}$ is an indicator for either an investment or a withdrawal transaction. $EventDay_{e,t_0+h}$ is an indicator equal to 1 on day $t_0 + h$, where t_0 is the day of the tweet. In this specification, the coefficient α_h estimates the treatment effect for event-day h. We include day of the week fixed effects ($\Lambda_{dow(t)}$) to absorb any variation from different levels of attention across days of the week, or from clustering of weekend transactions on Mondays. Because our data stacks 15 day event windows for each individual we include vectors of event (Γ_e) and individual (Ξ_i) fixed effects. We also include date fixed effects (ρ_t).

Since days in an event-window might also be days with other tweets in our database, the changes in trading on those days might be due to the other tweets. To account for this, we add indicator variables $\phi \mathbb{1}_{et}^{Pre\ tweet}$ which equal 1 if there is another tweet on day t in the pre periods. Next, we control for news coverage in the preceding days: $Factiva_{e,t_0-k}$ is the number of articles about cryptocurrencies on Factiva on day $t_0 - k$, and $StockTwits_{e,t_0-k}$ is the number of StockTwits posts about all coins in our sample on day $t_0 - k$. In both cases we include 7 lags to capture news about coins in the week preceding each celebrity tweet.

Lastly, if the event windows for two tweets overlap, the same user-day observations will appear twice in our specification and potentially artificially lower the standard errors. In response, we use a conservative approach and double-cluster the standard errors at the user and event level.

The timing of tweets themselves is not exogenous, as can be seen in Figure 2 where we plot the number of tweets at the monthly level along with the price of Bitcoin. However, most investors, especially retail investors on Albert, are not aware of the upcoming tweet. Therefore, by focusing on the reaction to the tweet, and by controlling for other contemporaneous cryptocurrency news and cryptocurrency prices, we isolate the response of retail investors to the celebrity tweets.

4.1 Dynamic effects

Figure 5 presents the dynamic treatment effects obtained by estimating equation (2) with an indicator for a crypto investment as the dependent variable. The coefficients are relative to day t-3. The coefficients are close to zero and statistically insignificant in the days leading up to a tweet, but investments increase on the day of the event. The effect is both statistically and economically significant, with the probability of an investment flow increasing by around 13.5% relative to the baseline investment rate in the week prior. This flow effect stays elevated for several days, eventually dying out. Given that flow into crypto may stay elevated as a result of additional celebrity tweets that occur following the original tweet, either caused by it or occurring independently, in Appendix Figure A2 we re-estimate equation (2), but control for $\Phi_{post}\mathbb{1}_{et}^{Post\ tweet}$ which is an indicator for other tweets by celebrities in our sample which occur in the post period. We find that, after controlling for other celebrity tweets in the Post period, the flow effect is short-lived, disappearing the following day.

To provide a better sense for the magnitude of the effects we compute the average persuasion rate across all tweets using again the formula from equation (1). In this case we observe the average fraction of individuals investing in cryptocurrencies leading up to the tweet: $y_C = 2.4\%$ which is the outcome mean in $t-1$ to $t-3$ from Table 6. We combine it with our point estimate $\alpha_0 = 0.269$ from column (1) of Table 6 to compute $y_T = 2.4\% + 0.269 = 2.7\%$. The only unobservable is the exposure rate (e.g., the share of individual investors that saw the tweet). If we assume an exposure rate of about 3%, we estimate a persuasion rate of about 9.2%. The large magnitude suggests celebrity messages can have wide-reaching implications for retail investors, even without any of the in-person interactions that are often behind the large persuasion rates in the literature.[14]

In Figure 6, we re-estimate the model separately for Bitcoin, Ether, DogeCoin, and the other coins in our sample (Ripple, Cardono, Polygon, and Shiba Inu). We find the same response of investment on the day of the tweet for each coin. Interestingly, the effect for

[14] For example, Gerber and Green (2000) find that face-to-face political mobilization is the most effective tool to increased voter turnout, followed by small effects from direct mail, and no effect by telephone calls.

DOGE starts on day $t-1$, a phenomenon that we corroborate using hourly data in Section 5. These estimates show that individual investors respond to celebrity tweets about cryptocurrencies by depositing money into their crypto investing accounts immediately following a tweet. Similarly, to the Appendix Figure A2 we re-estimate the model in Figure 6, but we control for $\Phi_{post}\mathbb{1}_{et}^{Post\ tweet}$ which equal 1 if there is another tweet on day t in the post period. The results are presented in the Appendix Figure A3. Again, we see that the effect of the original tweet is short-lived, lasting one business days.

4.2 Heterogeneity analysis

Next, we explore the characteristics of the individuals responding to celebrity financial advice from social media by either depositing additional funds in crypto accounts or withdrawing. For computational tractability we restrict our event window to 3 days before through 3 days after the event. Further, as the estimation results of equation (2) suggest that the effect is concentrated on the day of the event, we consider only day *zero* as the treatment period. That is, we estimate a variant of equation (2) as follows:

$$\begin{aligned} Outcome_{eti} = {} & \alpha_0 EventDay_{et_0} + \alpha_z (EventDay_{et_0} \times Z_i) \\ & + \beta Post_{et} + \beta_z (Post_{et} \times Z_i) + \Gamma_e + \Lambda_{dow(t)} \\ & + \Xi_i + \rho_t + \phi_{pre}\mathbb{1}_{et}^{Pre\ tweet} \\ & + \sum_{k=1}^{3} \delta_k Factiva_{e,t_0-k} + \sum_{k=1}^{3} \theta_k StockTwits_{e,t_0-k} + \epsilon_{eti}. \end{aligned} \tag{3}$$

Z_i are investor-level characteristics and the base levels of Z_i are absorbed by user fixed effects ξ_i. We additionally include $Post_{et}$ – an indicator marking post-treatment periods – and its interaction with characteristics Z_i. This allows us to interpret the estimated coefficients α_0 and α_z as the effect relative to the pre-treatment mean. We include all the controls for news that we used in the preceding analysis, adjusted to the estimation window.

Table 6 presents our baseline results. Column 1 shows that, on average, a celebrity tweet is associated with an increase of around 11% in the probability that a retail investor makes a cryptocurrency investment relative to the base level on the day of the tweet, compared to the average investment rate in the 3 days prior to the event. We also find that this effect persists in the post-period, albeit it's about half as strong as the effect on day t=0. Column 2 shows that the effect is driven by men, and column 3 shows that the estimated effect is increasing in income. Interestingly, the effect is also stronger for older users (column 4), and individuals with "excellent" credit scores (column 5). Column 6 includes all the individual characteristics together, because they are very likely to be correlated within individual. While the coefficients on income fall somewhat, the overall pattern is largely unchanged. One concern is that we might still be capturing news events on day t=0. In Table A7 we control for crypto news articles and for StockTwits mentioned on day t_0. While this is over controlling, as tweets could also be causing the news, which is part of the effect of the tweets, our main results on day t=0 survive. Furthermore, for completeness, appendix Table A6 repeats this exercise for withdrawals from cryptocurrency brokerages. While the baseline withdrawal rate is a much lower 0.37% we find men are slightly more likely to withdraw funds in response to celebrity tweets, and individuals with good and excellent credit scores are less likely to withdraw funds in response to celebrity tweets. However, other characteristics are largely insignificant, likely reflecting that withdrawals are relatively rare overall.

Next, we examine whether effects differ by the cryptocurrency mentioned in the tweet. Table 7 presents the results by interacting the EventDay indicator variable with whether the tweet was about Bitcoin, Ethereum, Doge, and Others. Overall, there are no strong differences in effect across coins: while the response to tweets about DogeCoin is largest, the interaction term is only marginally statistically significant. This difference also persists in the Post period. In the same vein, Table 8 explores whether different types of celebrities are associated with stronger effects. To this end, we include interactions of *EventDay* with different celebrity groupings: Celebrities (e.g., movie stars), musicians, sports stars, major internet-based influencers (e.g., Mr Beast, Jake Paul), finance-focused celebrities such as Mark Cuban and Mr Wonderful from Shark Tank ("Money"), and Elon Musk. Musicians seem to have greater influence than the other categories, whereas celebrities from Shark Tank (Mark Cuban and Mr Wonderful) have less influence. Importantly, the heterogeneity results in Table 8 also shows that our findings are not driven by responses to tweets from specific high-profile individuals, such as Elon Musk.

Interestingly, the lower response following tweets from celebrities with arguably more expertise in investing (e.g., finance-focused celebrities) is inconsistent with belief-based models, where agents should adjust for sender credibility. The results could also be driven by Marc Cuban's tweets being not consistently positive about crypto combined with a bias by agents to respond more to positive than negative messages. Our findings for retail investors in cryptocurrencies resemble the results in Malmendier and Shanthikumar (2007) for inexperienced individual investors, which underadjust for sender credibility and buy in response to optimistically biased recommendations.

Next, we examine whether there is heterogeneity by race and political affiliation in how individuals respond to celebrity tweets. While we don't directly observe the investors' race or political affiliation, we proxy for them by the shares of racial groups and registered voters of a given party in the population of the home county of the individual, as reported in the Albert data. Table 9 shows that investors living in counties with a higher Black population share are less likely to respond to celebrity tweets about cryptocurrencies, while people in areas with a high Asian population share are more likely to respond. By contrast, we find no economically or statistically significant differences by political affiliation.

Finally, we study whether the increase in investments into cryptocurrencies following a celebrity tweet is driven mostly by first-time crypto investors, or by existing crypto investors (extensive vs. intensive margins). If celebrities encourage first-time crypto investors enter the cryptocurrency market, their long-term impact on cryptocurrency flows is likely underestimated by our baseline models. Since we do not observe users' activity before mid-2020, we classify a deposit as as coming from a new crypto investor (i.e., the "extensive margin") if there are no cryptocurrency transactions by this user in the first 6 months of our sample. We present the results in Table 10. We find a strong positive effect of celebrity tweets on both extensive and intensive margins. A tweet increases the daily probability of a user making their first cryptocurrency investment by nearly 15.7% (column 4). The magnitude of the effect is slightly smaller in the case of intensive margin; here, on the day of a tweet the probability of an investment increases by over 11% relative to the baseline (column 6). A stronger effect for new investors in consistent with belief-based models, which predict that persuasion is more effective when the receiver is less certain about the true. Our stronger result for new investors is also in line with the literature showing that consumers buying a product for the first time are more sensitive to advertising than those who have bought the product in the past (Ackerberg, 2003, Simester et al., 2009).

5. Celebrities' Impact on Crypto Markets

In this section we explore the effects of celebrity tweets on the broader crypto markets. In particular, we first examine whether they affect the return and trading volume of the tweeted-about cryptocurrency. We then study how the size of trades changes in the hours around the tweets.

5.1 Event Study: returns and volume

We begin with an event study analysis that treats each tweet as an event, keeping a window spanning 72 hours before and after the time of each tweet. We then stack all events into a single dataset and estimate the following specification:

$$\begin{aligned} Outcome_{e,t} = & \sum_{h=-72}^{72} \alpha_h tweet_{e,t_0+h} \\ & + \Gamma_e + \Lambda_{dow(t)\times hour(t)} + \Phi \mathbb{1}_{e,t}^{Pre\ tweet} \\ & + \sum_{k=1}^{3} \delta_k Factiva_{e,t} + \Theta StockTwits_{e,t} + \epsilon_{e,t}, \end{aligned} \tag{4}$$

where the $Outcome_{et}$ for tweet e in period t is return or trading volume. α_0 is the estimated effect of the tweet in the hour of the tweet (day t_0), while the remaining α_h coefficients provide estimates for each of the hours in event-time preceding or following the tweet (i.e., from $t-72$ to $t+72$). Because our data stacks 1,102 separate event datasets,[15] one for each tweet, we include a vector of event (i.e., tweet) fixed effects (Γ_e) and cluster standard errors by event. We include day of the week times hour of the day fixed effects ($\Lambda_{dow(t)\times hour(t)}$) to absorb any variation coming from different levels of attention across days of the week and

[15] We have fewer events in this analysis relative to the individual-level analysis because our hourly data begins later.

times of the day. We also include a vector of indicators for days in the three day pre-period of our event window on which one of our celebrities tweets about the focal coin ($\mathbb{1}_{et}^{Pre\ tweet}$).

Finally, to account for the possibility that our results are driven by news regarding cryptocurrencies, we include controls for news coverage in the days and hours preceding each tweet. $Factiva_{e,t}$ captures the number of stories about cryptocurrencies on Factiva on each of the preceding 3 days, while $StockTwits_{e,t}$ separately controls for the number of StockTwits posts about all coins in our sample in the following time periods: $t-1$, $t-2$ to $t-4$, $t-5$ to $t-12$, $t-13$ to $t-24$, and days $t-2$ and $t-3$. In addition, we add controls for the number of StockTwits posts about the focal coin in the pre-period, using the same time bins.

Figure 7 plots the estimated α_h event-time coefficients obtained from pooling events for all coins, as well as separately for Bitcoin and Dogecoin, in the 72 hours (3 days) surrounding the tweet. The dependent variable is cumulative returns since $t-72$, the first hour in the event window. Panel (a) displays a generally positive return trend in cryptocurrency returns over our sample period. The trend appears to accelerate about 12 hours leading up to the tweet, with a slight jump in the hour of the tweet. The accelerated price increase continues for another approximately 12 hours before returning to its original pre-even trend. Panels (b) and (c) show similar patterns, with an increase in cumulative returns leading up to the tweet, and an eventual return to the pre-tweet trend. In particular, in Panel (b), the BTC price is quite stable leading up to the tweet, with an increase in returns starting about 36 hours prior to the tweet. The increase continues until about 12 hours after the tweet, at which point the cumulative returns stop increasing.[16] In Panel (c), we see a similar, but smoother increase in cumulative returns for DOGE, starting about 24 hours before the tweet, and flattening about about 12 hours after. Overall, while celebrity tweets appear to affect returns, the impact does not appear to be large, which is not surprising given the size of these crypto markets during our sample period.

A potential explanation for the pattern of increasing cumulative returns leading up to the tweet that we show in Figure 7 is that the celebrities in our sample may be tweeting in

[16] There is another increase in cumulative returns around 64 hours following the tweets. Since we only control for tweets leading up to the event, and not following the event, it is possible that it is the result of news following the tweet.

response to news about cryptocurrencies. However, our controls for news about cryptocurrencies from Factiva and StockTwits and for tweets by other celebrities about the coins in our sample in the hours leading up to each tweet help limit the confounding effects of other news.

Next, we examine the change in trading activity around celebrity tweets. As in Figure 7, we focus on the 72 hours before and after each tweet. The results for all coins are presented in Figure 8. The hours since the tweet are on the x-axis and the natural logarithm of trading volume (panel a) and of number of trades (panel b) are on the y-axis. All values are relative to the log trading volume and log number of trades at hour -72. Trading volume is quite stable until about 20 hours before the tweet, after which it begins to increase steadily. During the hour immediately following the tweet there is a jump of about 8 log points of trading volume, and it remains elevated, by about 10 log points relative to the pre-period baseline, for 24 hours following the tweet. While volume declines subsequently, it does not fall to its pre-tweet level in the event window. The pattern for the log number of trades in panel (b) is very similar, indicating that the trading results are unlikely to be driven by a small number of large trades.

Summarizing, using hourly return and trading volume data, we show increasing returns and trading volume in the hours leading up to the tweet, followed by a marked jump in trading activity immediately following the tweet. Returns also increase around the tweet, but to a much lesser extent.

5.2 Event Study: DogeCoin trades data

In the preceding section we used hourly data to examine prices and trading activity around the celebrity tweets; we now use trade-level data to study how trade size evolves around celebrity tweets. For data availability reasons we focus on DogeCoin and use transaction-level data for all DOGE-USDT trades from Binance.[17] This restriction means that, in this section we focus on 194 celebrity tweet events (vs. 1,102 in the preceding event study). We first examine the average dollar transaction size from a week before to a week after (168

[17] USDT is the ticker for the stablecoin Tether; this trade pair makes up around 68% all trades involving DOGE on Binance between July 2019 and the end of 2023.

hours) each celebrity tweet, using the same event study specification as in equation (4). Figure 9 presents the results. In the week leading up to the tweet there is a positive trend in transaction size; this accelerates around 24 hours before the tweet and we then observe a clear jump of 5 log points in event-hour 0. Afterwards, the average transaction size stays at an elevated level – around 15 log points above the level one week before the tweet – consistent with the elevated prices shown in Figure 7, Panel (c).

Next, we decompose the average dollar trade size into different subcategories. In particular, we focus on four bins of trade amounts: below \$200, between \$200 and \$1,000, between \$1,000 and \$10,000, and above \$10,000.[18] For each hour we calculate the share of trades in each size bin, and then estimate the model in equation (4) with these shares as dependent variables. We plot the coefficients for each of the four size bins in Figure 10.

We see some anticipation by market participants, as we saw for cumulative returns and trading activity for the sample that included all coins. The share of DOGE trades with transaction values below \$1,000 (Figure 9, panels a and b) decrease in the lead-up to celebrity tweets, with a distinct drop in the hour of the tweet. At the same time, the share of trades greater than \$1,000 (Figure 9, panels c and d) increases in advance of the tweet, with an especially clear spike in the share above \$10,000 in the hour of the celebrity tweets. These results suggest that either existing small-dollar investors start investing more per trade, or that larger investors move into the market for Dogecoin both in anticipation and as a response to celebrity tweets. Both forces may contribute to the results. On the one hand, we saw in the analysis in Section 4, Albert users (who are all small retail investors) increased their crypto investments in response to tweets. On the other hand, at least some of the investments over \$10,000, especially leading up to the celebrity tweets, are likely to be the trades of wealthier investors who are potentially aware of the upcoming tweet.

Given that 34% of celebrity tweets about Dogecoin are written by Elon Musk, we want to ensure that the above results are not driven by his tweets. Therefore, in Appendix Figure A6 we rerun the same analysis excluding Musk's tweets. We find that the results are consistent

[18] \$200 is the median transaction amount in the data, \$1,000 is the 85th percentile, and \$10,000 is percentile 99.3 (the 99th is \$8,100). We chose these cutoffs as they are intuitive round numbers, but results are similar if we use the 75th percentile and the 99th percentiles instead, or indeed any nearby percentiles. For reference, the mean transaction size is around \$720 and the standard deviation is \$2,900.

with the full sample and even stronger in some instances. We still find a clear drop in the share of trades below $1,000, starting before the celebrity tweet. The figures also show that the share of trades larger than $1,000 and especially above $10,000 increase in the hours leading up to the celebrity tweets and stay elevated following the tweets. While the increase in the share of large trades leading up to the celebrity tweets – both including and excluding those of Elon Musk – could be driven by other cryptocurrency news or tweets, our specification controls for cryptocurrency news, prior celebrity tweets, and the number of StockTwits posts about Doge and about other coins in the hours and days leading up to the tweet; this greatly reduces the scope for other news to be driving these patterns .

In summary, in this section we find that cumulative returns and trading volume rise in the days leading up to the celebrity tweets, spike in the hour of the tweet, and then remain elevated following the tweets. Using transaction-level data for Dogecoin, we find that the increase is driven primarily by larger trades. In the next section we simulate various buy/sell times, and estimate returns for investors who trade before versus after the celebrity tweets.

6. The quality of Celebrities' Financial "Advice"

In the last two sections we have shown that individual investors trade based on crypto-related tweets by real-world celebrities. A question remains whether the investors would have been better off buying based on the tweets or trading on their own. To answer this question we begin by examining the performance of trades in the days and hours surrounding the tweets, and compare the performance of those trades to counterfactual trading opportunities.

Since we don't observe the exact times individuals traded based on the tweets, we examine the performance of trades around the tweets by constructing a grid of returns of certain buying intervals before and after the tweet, and selling intervals after the tweets. The first set of results are presented in Figure 11, Panel A. On the x-axis are times of purchase relative to the tweet, and on the y-axis are times of sale relative to the tweet. For example, the most left bottom cell is the return from buying the coin 48 hours prior to the tweet, and selling at the end of the hour of the tweet. The rest of the cells in that column are returns of buying 48 hours before the tweet and selling 1 hour, 2 hours, 6 hours, etc, up to 2 weeks after the tweet.

The 2-week cutoff is based on the 12-day median holding period of cryptos by retail investors at a retail brokerage eToro (Kogan, Makarov, Niessner, and Schoar, 2023). Investors who purchased the coin before the tweet was published were either 'insiders' that were aware that a tweet was coming or people who purchased the coin by chance. Most investors would not have advance notice of the impending tweet, and thus would have purchased the coin in the post-tweet period. This is consistent with the elevated post-tweet volumes and number of trades that we document in Sections 4 and 5.

In Figure 11, Panel A, the deeper the red color, the lower are the returns. We separate trades where the purchase was in the *pre* period and the sale in the *post* period (pre-post trades) from trades where both the purchase and the sale occurred in the *post* period (post-post trades). All the columns to the left of 0 on the x-axis represent returns for pre-post trades, and the columns to the right of 0 represent returns for post-post trades. Visually the returns get smaller (darker red) as we move from left to right, suggesting the later an investor buys the coin (controlling for the selling time) the smaller the returns will be.The average gross return of the pre-post period is 2.8% and in the post-post period it's 0.4%. The difference is statistically significant at the 1% level.

While the gross return is significantly higher if the purchase occurred before the tweet, it is still positive if the coin was acquired after the tweet. To compute a more precise measure of investors returns from following celebrity tweet we account for the cost of trading cryptocurrencies. While there is variation across companies and even within companies based on trading volumes (usually volume-based rebates), we focus on a representative trader with Coinbase, which is the most popular platform in the US. The average fee for an investor which has less than $10K in trading in the last 30 days is about 50 bps.[19] We think this is the fee most retail investors will likely pay given the median trading size of $200 in our trade-level DogeCoin data and the evidence in Kogan et al. (2023). Companies like Robinhood offering 0% fee on cryptocurrency trades do not execute orders at current market prices, earning the spread between effective transaction prices and quotes to the customer. With these caveats in mind, Panel B of Figure 11 shows the return for a representative trader.

[19] See https://help.coinbase.com/en/exchange/trading-and-funding/exchange-fees for Coinbase and https://www.fool.com/investing/stock-market/market-sectors/financials/cryptocurrency-stocks/transaction-fees/ for a comparison across companies.

The average net return of the pre-post period is down to 2.3% and in the post-post period it is now slightly negative at -0.1%. Hence a representative retail investor trading following celebrity tweets would have made negative return after accounting for transaction costs.

Finally, when considering the gross return of 0.4% it's important to compare it to the counterfactual return - what would have the return been had the investor traded on their own and not followed the tweet. While the exact counterfactual is not observable, we construct what we think is a reasonable counterfactual. Most notably, we assume that the investors would have investment in Bitcoin rather than in the cryptocurrency mentioned in the tweet.[20] Hence, we construct abnormal returns - returns relative to Bitcoin, which is often viewed as the market return in cryptocurrencies (Liu and Tsyvinski, 2021). We repeat the analysis similar to Panel A, except we use abnormal returns – returns minus the 'market' return. We present the results in Figure 11, Panel C. Similar to raw returns, the color gets darker red as we move from left to right, suggesting that abnormal returns get smaller the later an investor buys the coin relative to the tweet. Comparing the pre-post trades to post-post trades, the average abnormal return for the pre-post trades is 1.9%, while the average abnormal return for the post-post trades is -0.5%. The results are statistically significant at the 1% level. Even if trading costs for Bitcoin and other less popular cryptocurrencies are identical, this result suggests that retail investors trading after celebrity tweets would have been better off buying the "market" (i.e., Bitcoin) rather than the cryptocurrency mentioned in the tweet.[21]

7. Conclusion

As investors look to social media for news and financial advice about cryptocurrencies, a new group of 'financial advisors' has emerged with an unprecedented reach – real-world celebrity influencers. We combine survey responses and transaction-level data with real-world celebrities' Twitter crypto-related posts to study how celebrity endorsements shape households' financial decisions. We find that a celebrity tweet is associated with a higher probability of investing in cryptocurrencies, with the effect being stronger for men, wealthier,

[20]Since we can't use Bitcoin returns to calculate abnormal returns for Bitcoin trades, for tweets about Bitcoin we use Ethereum as the counterfactual return, since it's the second most-traded coin.

[21]Notice that if trading cost for less liquid currencies relative to Bitcoin are relatively higher the net abnormal returns are even lower.

and older users, and users with good credit scores. We further find that aggregate trading volume and the number of trades increases on the day of the tweet and stays elevated for the following several days. Interestingly that increase is driven mostly by larger trades. Finally we show that investors who bought the coins after the tweet would have been better off buying Bitcoin (or Ethereum in the case of a Bitcoin tweet) instead.

As the number of lawsuits against celebrities mounts, it's important to understand whether and who actually follows the celebrities' advice and do they benefit from it. Our study takes a step towards understanding who is trading following the celebrity tweets and how the markets react to these promotions. It also highlights the reach these new breed of 'financial advisors' have, and potential need for regulation of the financial advice provided outside the traditional financial advising sector.

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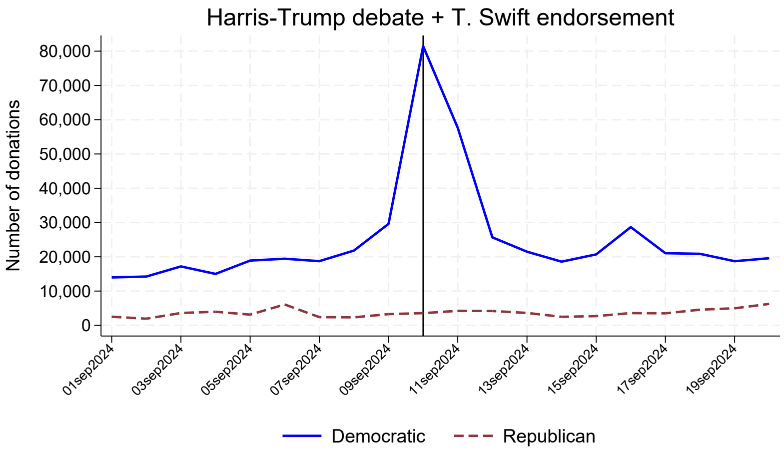
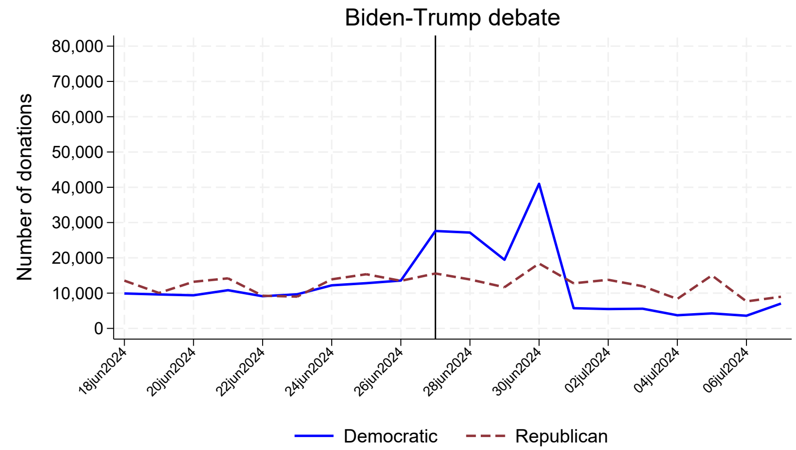
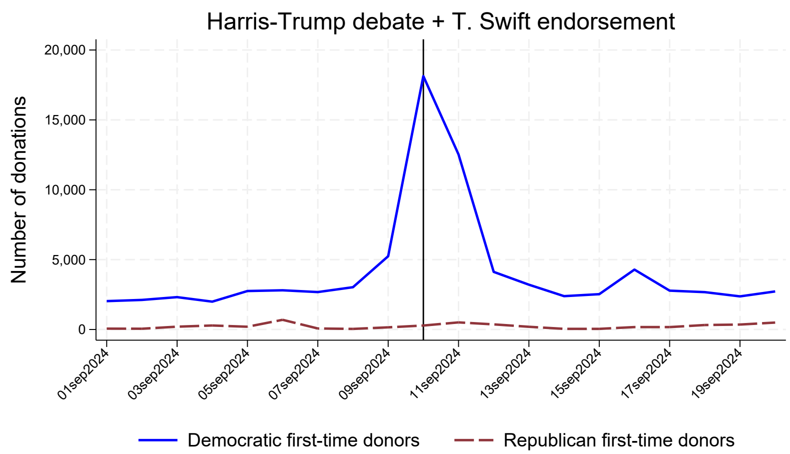
Figure 1: Political Donations around Presidential Debates



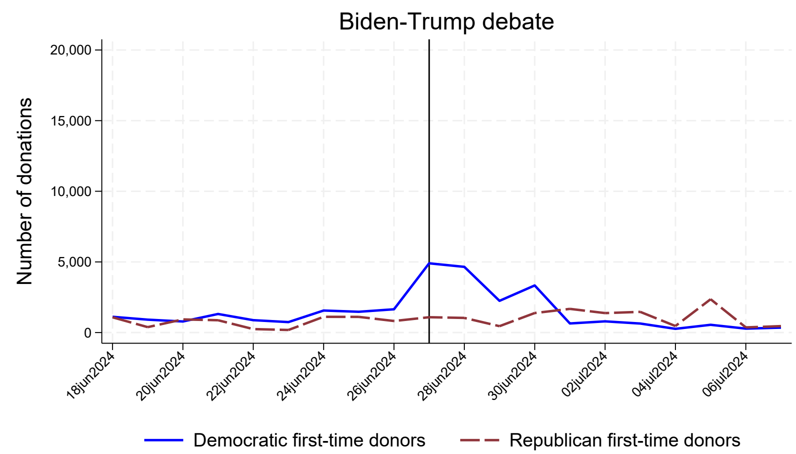
(a) All donors



(b) All donors



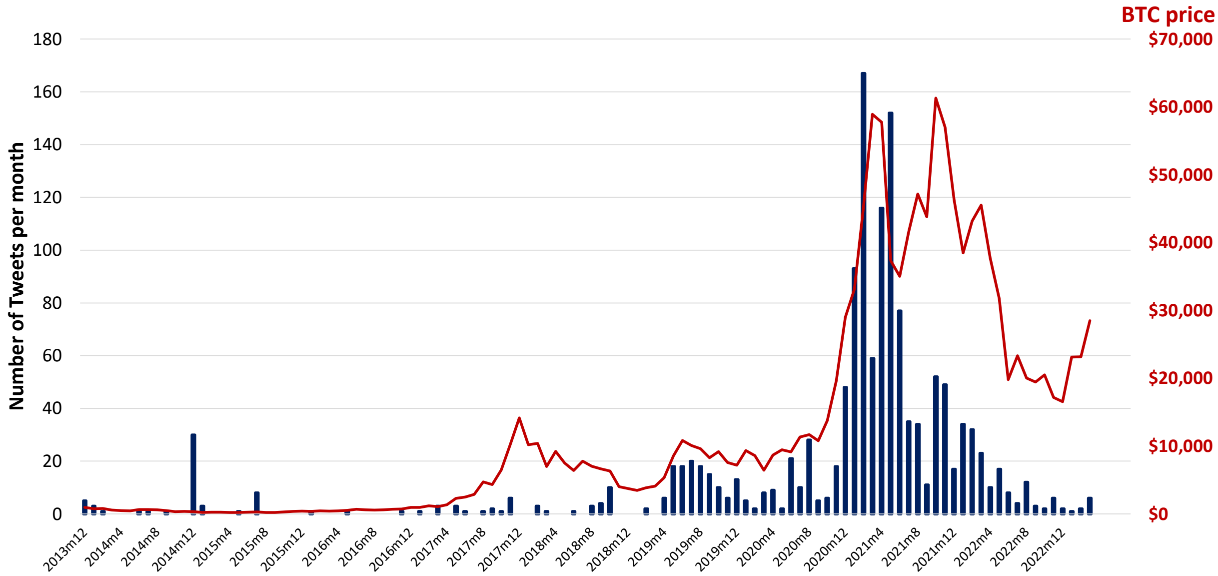
(c) First-time donors only



(d) First-time donors only

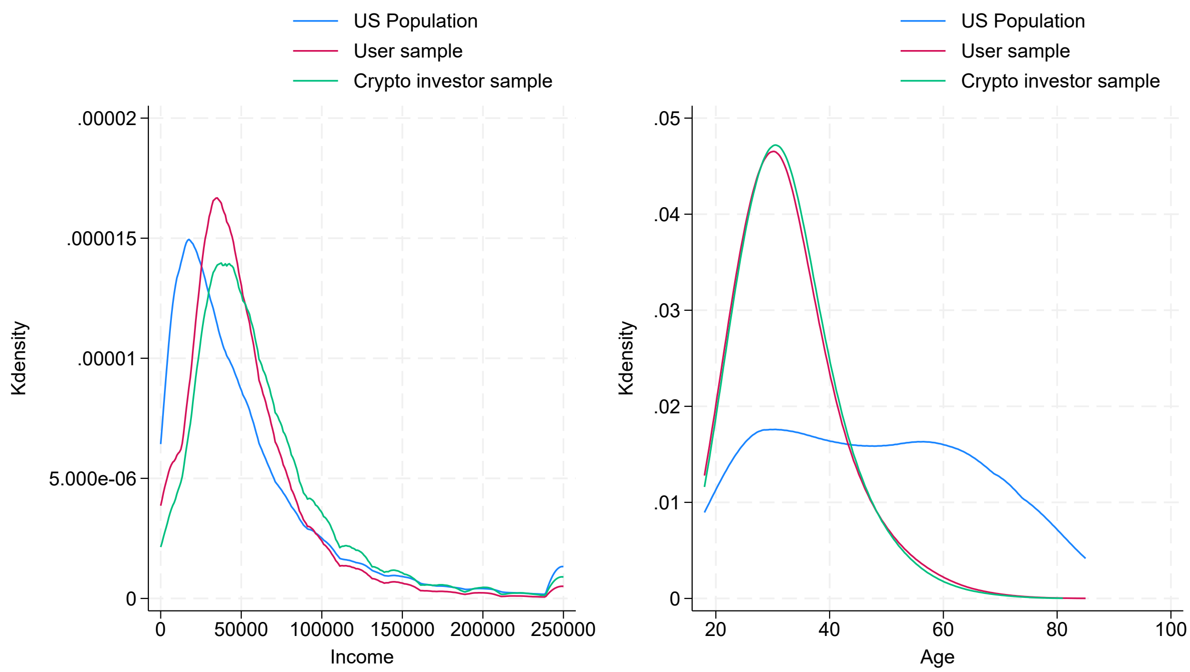
Note: These plots report the number of donations by individuals to Democratic and Republican-identified political committees reported by the Federal Election Commission (FEC) around both U.S. Presidential debates in 2024. The Harris–Trump occurred on September 10; the Biden–Trump debate occurred on June 27. Musician Taylor Swift endorsed Vice-President Harris as a Presidential candidate on Instagram around 40 minutes after the second debate concluded (link). There were no widely-reported celebrity endorsements of President Biden or of President Trump around either debate. Panels (a) and (b) include all individual donors in the FEC's individual contributions file for 2023-4. Panels (c) and (d) include only the first donation of individuals in the individual contributions file, i.e., before donating in the event window, these donors (identified by name, city and state) have not donated to any committee registered with the FEC in 2023-4. The share of total donations (number) made up of first-time donors goes from around 14% at the beginning of the window to 22% on the day of the Harris-Trump debate, then falls back to 14% by the end of the window, a 50% increase in the new donor share.

Figure 2: Number of Tweets and Bitcoin price



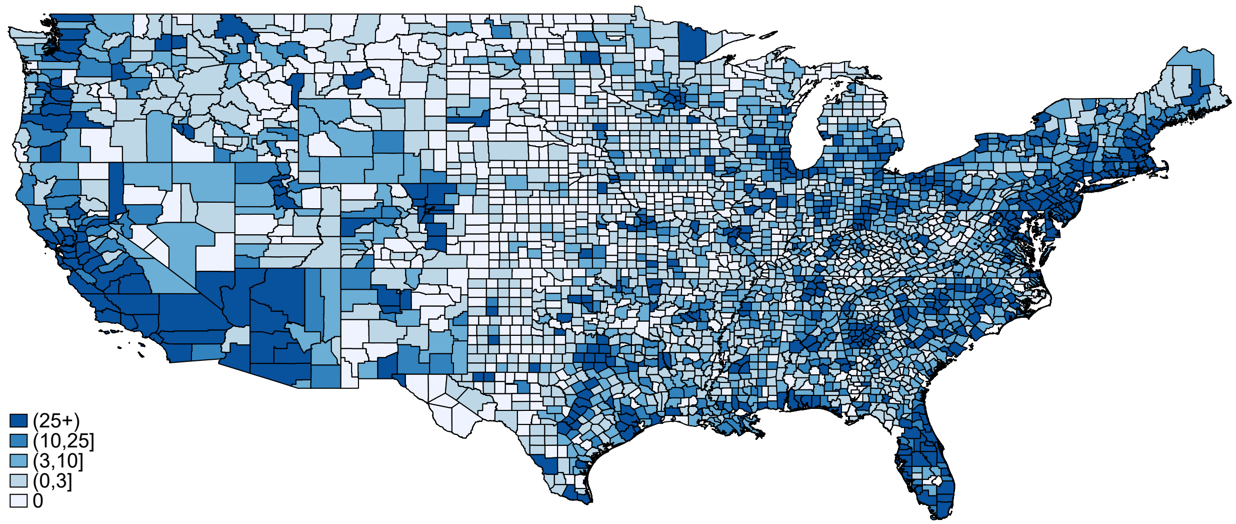
Note: This figure displays the frequency of celebrity tweets in our sample and the price of Bitcoin (BTC) over time.

Figure 3: Comparing our individual data sample to the U.S. population



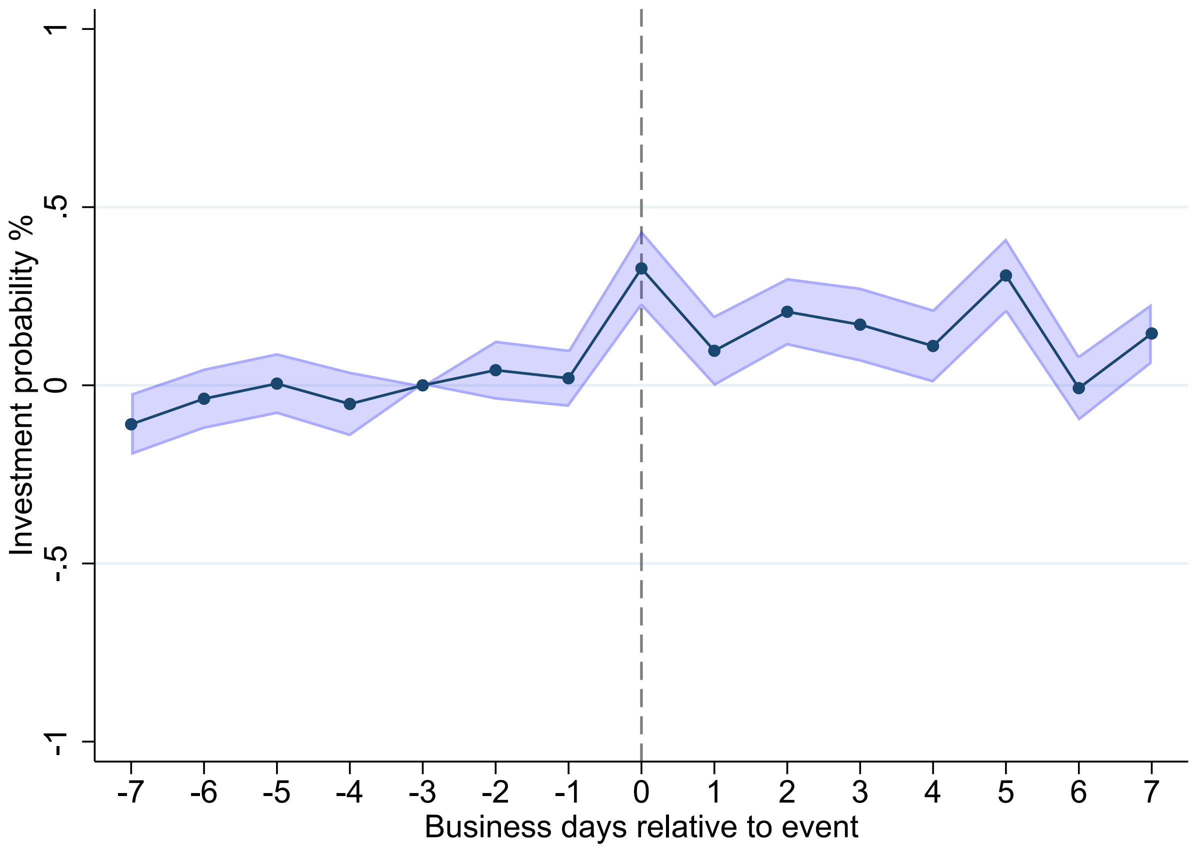
Note: U.S. data from the 2020 Current Population Survey.

Figure 4: Geographical distribution of users in our sample



Note: This figure presents the geographical distribution of sample of aggregator app users at the county level.

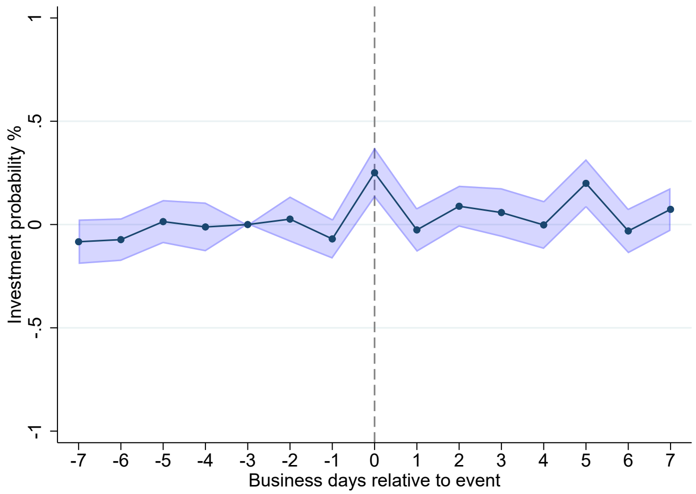
Figure 5: Dynamic investment response



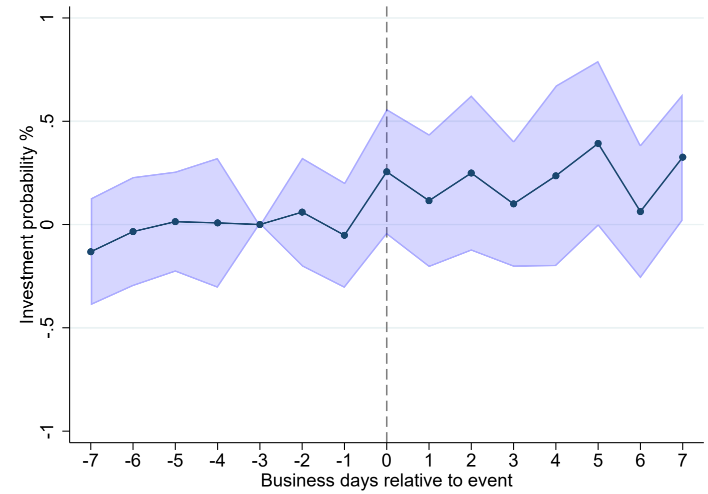
Note: This figure plots the estimated treatment effect coefficients from equation 2. The dependent variable is an investment indicator. Day -3 is the reference category. 95% confidence intervals double clustered at the user and day level.

Figure 6: Effects by coin

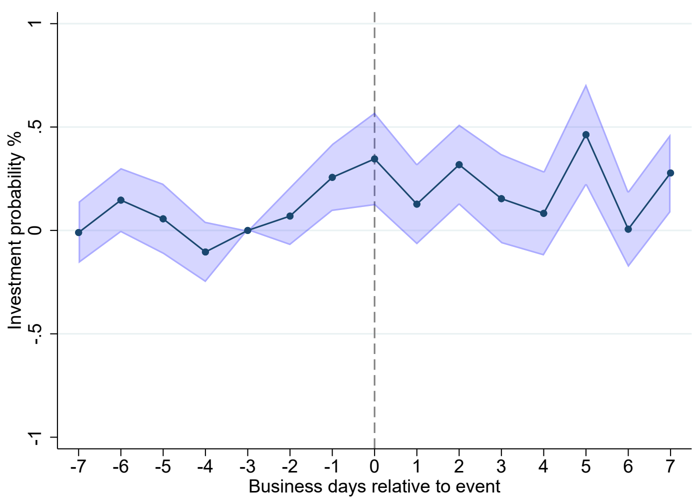
(a) Bitcoin



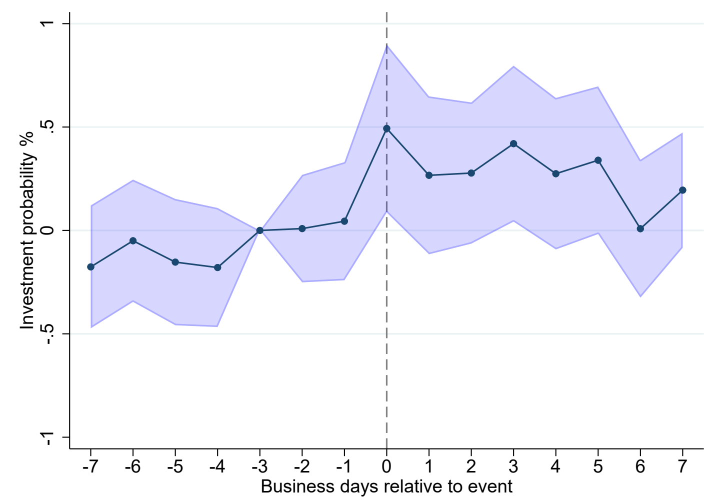
(b) Ether



(c) DogeCoin

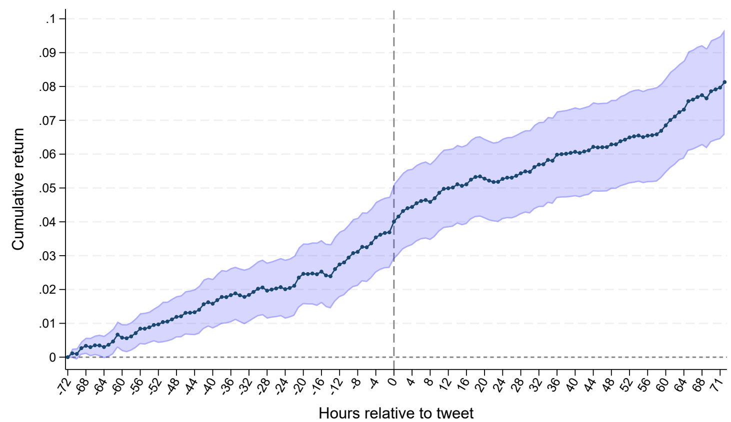


(d) Other coins

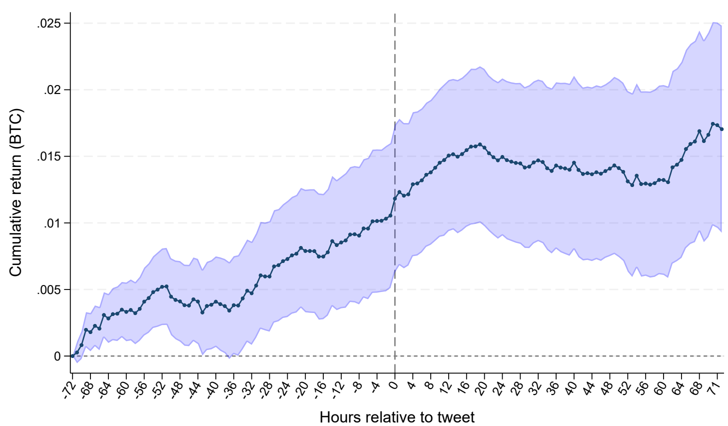


Note: This figure plots estimated treatment effect coefficients from equation 2. The dependent variable is an investment indicator. Subfigure (a) plots the results for Bitcoin, (b) for Ethereum, (c) for Dogecoin, and (d) for the other coins in our sample (Ripple, Cardono, Polygon, and Shiba Inu). Day -3 is the reference category. 95% confidence intervals double clustered at the user and day level.

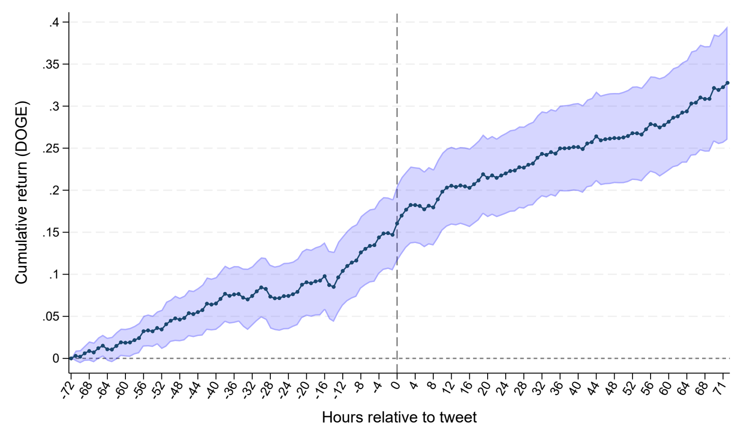
Figure 7: Cumulative Returns around tweets



(a) All Coins



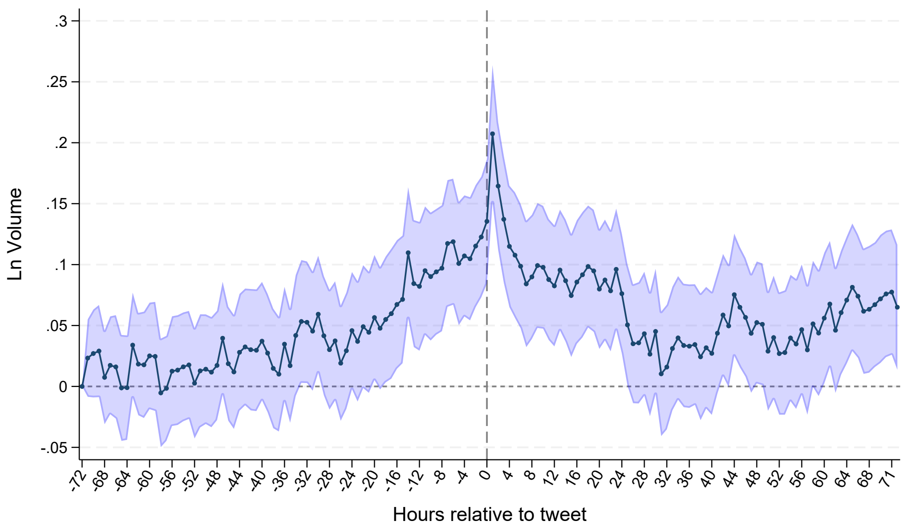
(b) Bitcoin (BTC)



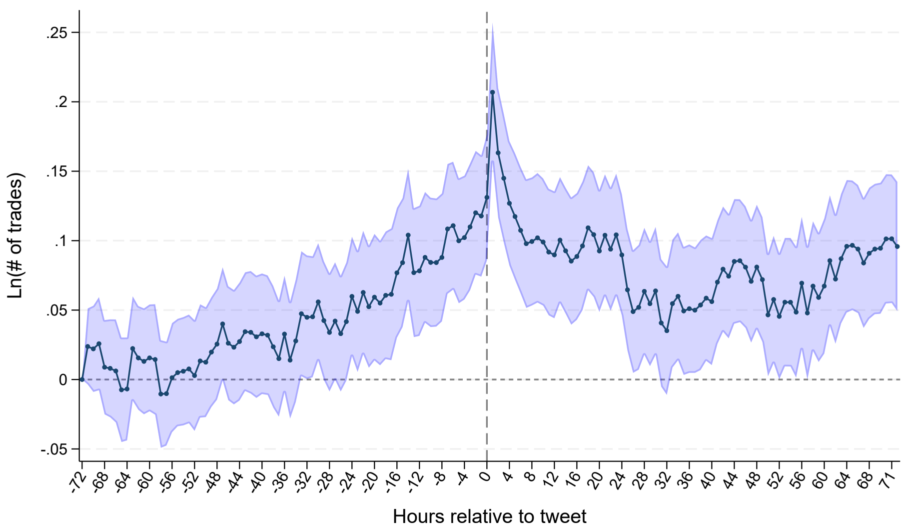
(c) DogeCoin (DOGE)

Note: These figures plot α_t event-time coefficients from equation 4 for cryptocurrency returns on Binance. These correspond to coefficients from regressing cumulative returns on hourly event-time indicators in a +/- 3 day window (72 hours) around celebrity tweets for all coins. Equation 4 details the additional control variables. All values are relative to log volume at hour -72. A cumulative return of 0.01 corresponds to a return of 1 percentage point. Standard errors are clustered by event (tweet); 95% confidence intervals.

Figure 8: Trading Around Tweets



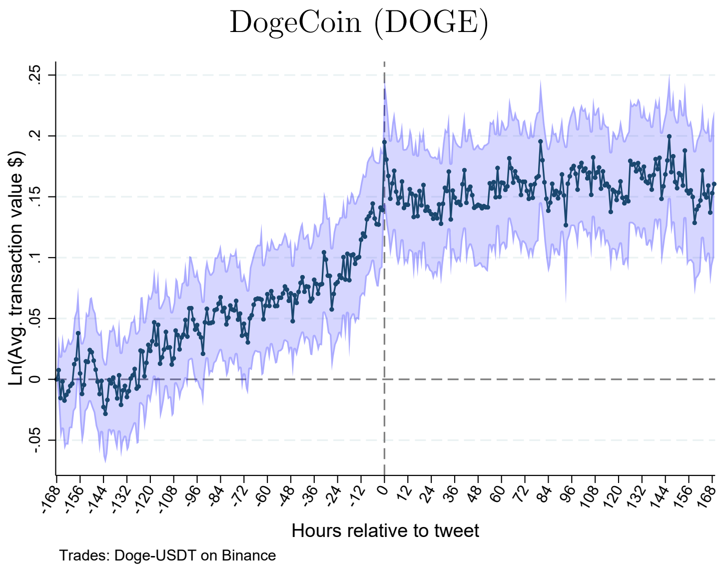
(a) Log Trading Volume



(b) Log Number of Trades

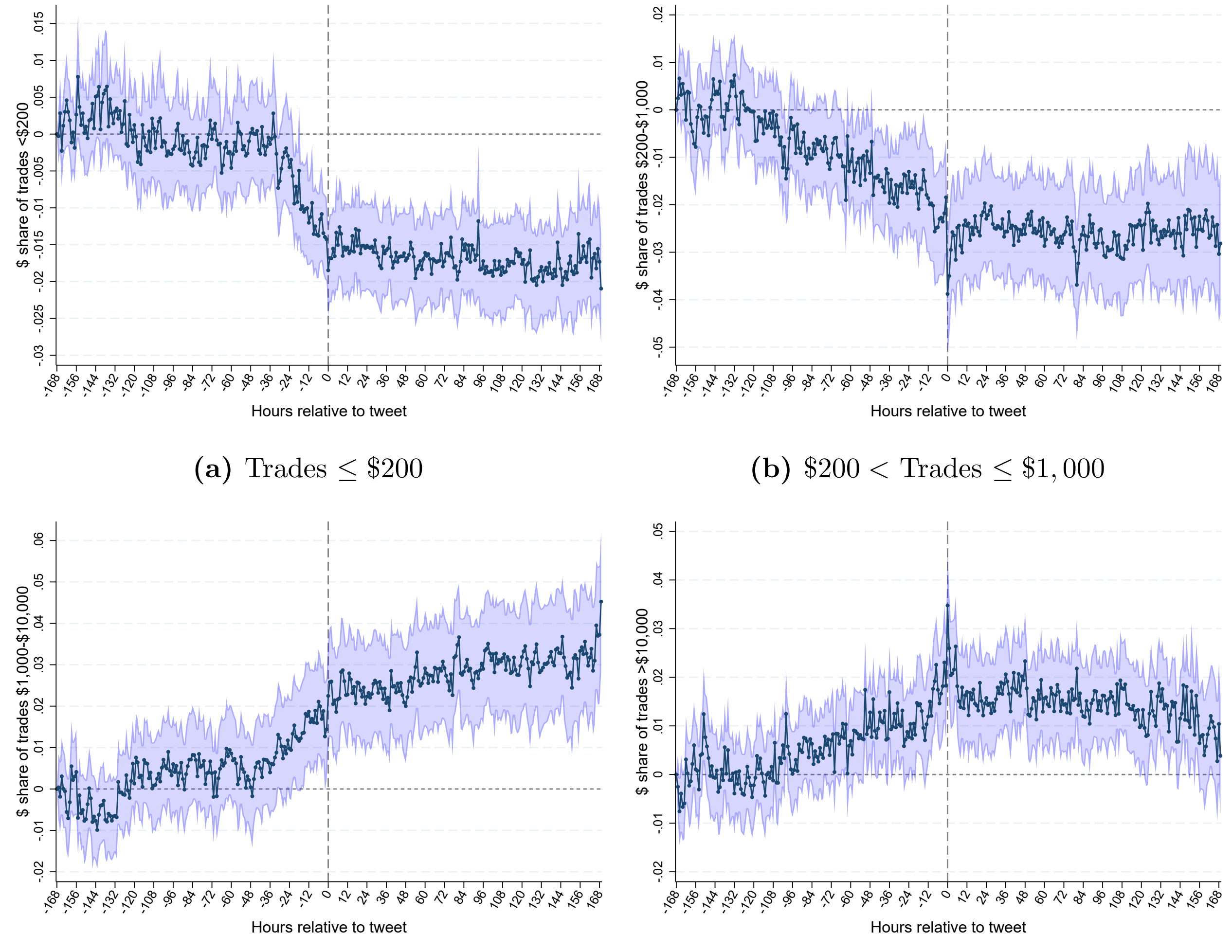
Note: This figure plots α_t event-time coefficients from equation 4 for cryptocurrency trading on Binance. These correspond to coefficients from regressing log trading volume (panel a) and log number of trades (panel b) on hourly event-time indicators in a +/- 3 day window (72 hours) around celebrity tweets for all coins. Equation 4 details the additional control variables. All values in Panel a) are relative to log volume at hour -72, and in Panel b) relative to log number of trades at hour -72. Standard errors are clustered by event (tweet); 95% confidence intervals.

Figure 9: Log Average Transaction Size



Note: This figure plots α_t event-time coefficients from equation 4. These correspond to coefficients from regressing the natural logarithm of average transaction amounts on hourly event-time indicators in a +/- 1 week window (168 hours) around celebrity tweets about DogeCoin. Equation 4 details the additional control variables. All values are relative to log volume at hour -168. Standard errors are clustered by event (tweet); 95% confidence intervals.

Figure 10: Share of Dogecoin trades by trade size



(a) Trades $\leq \$200$

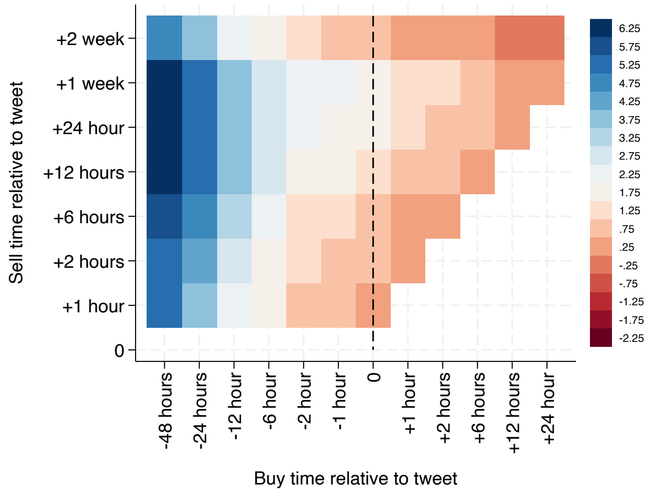
(b) $\$200 <$ Trades $\leq \$1,000$

(c) $\$1,000 <$ Trades $\leq \$10,000$

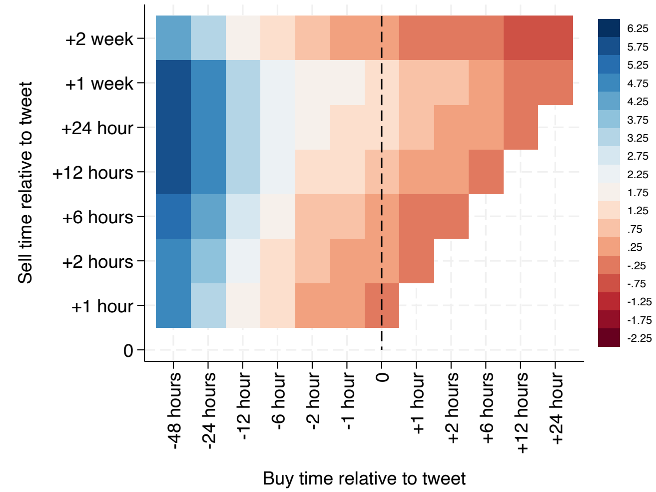
(d) Trades $> \$10,000$

Note: This figure presents four event studies of the relative share of DogeCoin trades in bins of trade size (in $) around a celebrity tweet occurring in hour 0. Each graph plots hourly event time coefficients from a regression of the share of trades in a given bin on hourly event time indicators, fixed effects (for event and for day-of-week × hour-of-day) and controls for (i) number of posts about DogeCoin on StockTwits (in hour t-1, hours t-2 to t-4, t-5 to t-12, t-13 to t-24, and for each day in t-2 through t-7); (ii) number of posts about all cryptocurrencies on StockTwits (in same bins as (i)); and (iii) number of articles about cryptocurrencies on Factiva (for each day in t-1 through t-7). We stack each of the 194 events in the sample and estimate all coefficients in each graph in a single regression. An event is a one week window (-/+168 hours) either side of a celebrity tweet about DogeCoin. The omitted category is hour t-168. Standard errors are clustered by event (tweet); 95% confidence intervals. Trades are from Binance.

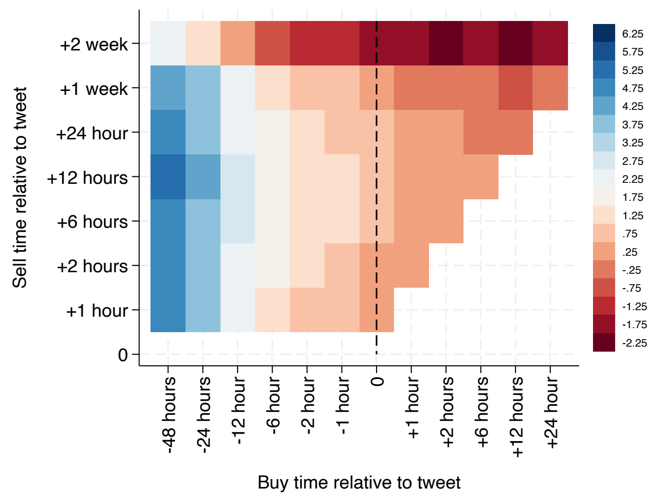
Figure 11: Trading Returns



(a) Gross Returns



(b) Net Returns



(c) Abnormal Returns

Note: This figure presents returns to trading around celebrity tweets. The x-axis shows when a trade was initiated relative to the tweet, the y-axis shows when a trade was closed out, relative to the tweet. In Panel A, the columns to the left of '0' on the x-axis represent returns to trades that were opened *before* the tweet and closed out *after* the tweet. The columns to the right of 0 represent returns to trades that were opened *after* the tweet and closed out *after* the tweet. In Panel B, we consider net returns after transaction costs. In Panel C, we consider abnormal returns - returns on the coins minus the return on BTC. For trades in BTC we subtract the returns on ETH.

Table 1: Summary Statistics

Panel A

Crypto Name	Freq.	Percent
Bitcoin (BTC)	874	61.77%
Cardano (ADA)	31	2.19%
DogeCoin (DOGE)	246	17.39%
Ether (ETH)	102	7.21%
Polygon (MATIC)	14	0.99%
Ripple (XRP)	54	3.82%
Shiba Inu (SHIB)	94	6.64%
Total	1,415	100%

Panel B

Gender	Freq.	Percent
Female	27	1.91%
Male	1,388	98.09%

Panel C

Race	Freq.	Percent
Asian	2	0.14%
Black	578	40.85%
White	835	59.01%

Panel D

Celebrity Type	Freq.	Percent
Celebrity	270	19.08%
Musician	185	13.07%
Internet	227	16.04%
Shark Tank	224	15.83%
Elon Musk	132	9.33%
Sports	377	26.64%

Note: This table presents the summary statistics in our data. Panel A displays the number of tweets per coin in our main dataset. Panels B, C, and D, summarize the number of tweets by celebrities' gender, race, and type.

Table 2: User summary statistics - aggregator app

	Count	Mean	Std	p10	p50	p90
Full sample						
Demographic variables						
Gender: Male	80,912	0.29	0.45	0.00	0.00	1.00
Gender: Female	80,912	0.41	0.49	0.00	0.00	1.00
Gender: Other/not-reported	80,912	0.30	0.46	0.00	0.00	1.00
Age	80,891	32.75	8.32	24.00	31.00	44.00
Income ($1,000s)	80,786	51.38	42.52	14.80	42.64	94.60
Kids	80,507	0.79	1.24	0.00	0.00	3.00
Credit score: missing	80,912	0.44	0.50	0.00	0.00	1.00
Credit score: poor	80,912	0.20	0.40	0.00	0.00	1.00
Credit score: average	80,912	0.15	0.35	0.00	0.00	1.00
Credit score: good	80,912	0.09	0.28	0.00	0.00	0.00
Credit score: excellent	80,912	0.12	0.32	0.00	0.00	1.00
Married	80,912	0.24	0.42	0.00	0.00	1.00
Gambler	80,912	0.13	0.34	0.00	0.00	1.00
Stock investor: crypto	80,912	0.30	0.46	0.00	0.00	1.00
Stock investor: wo crypto	80,912	0.11	0.31	0.00	0.00	1.00
Crypto investors						
Gender: Male	15,904	0.47	0.50	0.00	0.00	1.00
Gender: Female	15,904	0.29	0.45	0.00	0.00	1.00
Gender: Other/not-reported	15,904	0.24	0.43	0.00	0.00	1.00
Age	15,902	32.81	7.86	25.00	31.00	44.00
Income ($1,000s)	15,889	62.49	50.69	20.00	50.00	117.00
Kids	15,862	0.69	1.17	0.00	0.00	2.00
Credit score: missing	15,904	0.35	0.48	0.00	0.00	1.00
Credit score: poor	15,904	0.19	0.39	0.00	0.00	1.00
Credit score: average	15,904	0.18	0.38	0.00	0.00	1.00
Credit score: good	15,904	0.11	0.31	0.00	0.00	1.00
Credit score: excellent	15,904	0.17	0.37	0.00	0.00	1.00
Married	15,904	0.26	0.44	0.00	0.00	1.00
Gambler	15,904	0.21	0.41	0.00	0.00	1.00
Stock investor: crypto	15,904	0.58	0.49	0.00	1.00	1.00
Stock investor: wo crypto	15,904	0.20	0.40	0.00	0.00	1.00

This table presents the summary statistics for the main user-level variables from the aggregator application sample. *Gambler* is a dummy variable marking users who transacted at least $X with four major online betting services. *Stock investor: crypto* is a dummy indicating investors who use brokerage services focused on stocks but also offering cryptocurrencies (e.g., Robinhood) while *Stock investor: wo crypto* indicates users of traditional brokerages that do not offer cryptocurrency investments. *Income* is trimmed at $1 million. *Number of kids* is trimmed at 8 and *Age* at 85 to mitigate the noise coming from unrealistic misreporting. The upper panel includes all users in the sample and the lower panel is restricted to crypto investors.

Table 3: Investor-level summary statistics

	Count	Mean	Std	p10	p50	p90
Investor-level variables						
Total investments $	15,904	3018.21	17044.23	7.00	220.00	5285.49
Total withdrawals $	15,904	1564.53	11498.86	0.00	0.00	2006.53
Number of investments	15,904	18.20	63.44	1.00	3.00	39.00
Number of withdrawals	15,904	2.65	10.30	0.00	0.00	6.00
Transaction-level variables						
Investment $	289,409	165.86	942.23	11.60	33.00	100.00
Withdrawal $	42,086	591.22	4040.80	30.83	101.53	387.38

This table presents summary statistics for cryptocurrency-related variables. The upper panel shows investor-level total values of cryptocurrency deposits and withdrawals in the entire sample period as well as the number of transactions per user. The bottom panel presents summary statistics at the cryptocurrency transaction level, for investments and withdrawals separately.

Table 4: Who follows Celebrity Influencers' financial advice? Survey Evidence

	Own crypto	See Emax post	Invest after post
	(1)	(2)	(3)
Female	-0.14***	-0.11***	-0.07*
	(0.02)	(0.02)	(0.04)
Age: 35-44	-0.00	-0.06**	0.07
	(0.03)	(0.03)	(0.06)
Age: 45-64	-0.18***	-0.18***	-0.15***
	(0.02)	(0.02)	(0.05)
Age: 65+	-0.25***	-0.19***	-0.23***
	(0.03)	(0.03)	(0.06)
Hispanic	0.06*	0.07**	0.06
	(0.03)	(0.04)	(0.07)
Black	0.11***	0.09***	-0.06
	(0.03)	(0.03)	(0.05)
Bachelor	-0.00	0.01	0.02
	(0.02)	(0.02)	(0.05)
Post-grad	0.05**	0.03	0.08
	(0.02)	(0.02)	(0.06)
Self-employed	0.12***	0.07**	0.01
	(0.04)	(0.04)	(0.06)
Homemaker	0.01	-0.06*	-0.10
	(0.03)	(0.03)	(0.07)
Unemployed	-0.05**	-0.09***	-0.11**
	(0.03)	(0.03)	(0.06)
Income: 50-100	0.03**	0.02	-0.01
	(0.02)	(0.02)	(0.04)
Income: >100	0.08***	0.05**	0.05
	(0.02)	(0.02)	(0.06)
Suburban	-0.07***	-0.10***	-0.10**
	(0.02)	(0.02)	(0.04)
Rural	-0.08***	-0.08***	-0.12**
	(0.02)	(0.02)	(0.05)
Region FE	Yes	Yes	Yes
Outcome mean	0.17	0.18	0.19
R^2	0.18	0.13	0.20
Obs.	2200	2200	399

Note: The table report the results of a linear probability model. In column (1) the dependent variable is an indicator equal to one if the respondent holds any cryptocurrencies. In column (2) the dependent variable is an indicator equal to one if the respondent sees the Instagram post by Kim Kardashian. In column (3) the dependent variable is an indicator equal to one if the respondent invests in Ethereum Max after seeing the Instagram post by Kim Kardashian. Robust standard errors in parentheses; *** 1%, ** 5%, * 10% significance level.

Table 5: Opinion about influencers and investment

	Own crypto	See Emax post	Invest after post
	(1)	(2)	(3)
Opinion about Kim Kardashian:			
Negative	-0.01	-0.06***	-0.11**
	(0.02)	(0.02)	(0.05)
Positive	-0.02	0.11***	0.10*
	(0.02)	(0.03)	(0.06)
Opinion about Elon Musk:			
Negative	0.00	0.02	-0.06
	(0.02)	(0.02)	(0.06)
Positive	-0.02	0.01	-0.05
	(0.02)	(0.02)	(0.05)
Demographics	Y	Y	Y
Opinion on crypto	Y	Y	Y
Outcome mean	0.17	0.18	0.19
R^2	0.40	0.21	0.26
Obs.	2,200	2,200	399

Note: The table report the results of a linear probability model. In column (1) the dependent variable is an indicator equal to one if the respondent holds any cryptocurrencies. In column (2) the dependent variable is an indicator equal to one if the respondent sees the Instagram post by Kim Kardashian. In column (3) the dependent variable is an indicator equal to one if the respondent invests in Ethereum Max after seeing the Instagram post by Kim Kardashian. Demographics include all the demographics variables in Table 4. Opinion on crypto includes respondent opinion on coinbase, robinhood and cryptocurrencies in general. Robust standard errors in parentheses; *** 1%, ** 5%, * 10% significance level.

Table 6: Effect of Tweets on Cryptocurrency Deposits

	(1)	(2)	(3)	(4)	(5)	(6)
EventDay	0.269***	0.137**	0.144***	0.028	0.203***	-0.218***
	(0.053)	(0.054)	(0.053)	(0.062)	(0.059)	(0.079)
EventDay × Male		0.227***				0.241***
		(0.042)				(0.043)
EventDay × Income>40k			0.123***			0.050
			(0.036)			(0.036)
EventDay × Income>80k			0.287***			0.139***
			(0.055)			(0.053)
EventDay × Age>25				0.205***		0.177***
				(0.045)		(0.046)
EventDay × Age>35				0.368***		0.325***
				(0.060)		(0.060)
EventDay × CS: Average					0.085	0.083
					(0.052)	(0.052)
EventDay × CS: Good					0.092	0.092
					(0.059)	(0.059)
EventDay × CS: Excellent					0.239***	0.211***
					(0.063)	(0.064)
Post	0.121***	0.120***	0.102**	0.101**	0.098**	0.074*
	(0.046)	(0.044)	(0.044)	(0.046)	(0.045)	(0.045)
Post × Male		0.008				0.007
		(0.015)				(0.015)
Post × Income>40k			0.021			0.015
			(0.013)			(0.013)
Post × Income>80k			0.040*			0.025
			(0.021)			(0.019)
Post × Age>25				0.021		0.011
				(0.017)		(0.017)
Post × Age>35				0.022		0.006
				(0.021)		(0.021)
Post × CS: Average					0.033*	0.031*
					(0.017)	(0.017)
Post × CS: Good					0.033	0.030
					(0.021)	(0.021)
Post × CS: Excellent					0.068***	0.063**
					(0.026)	(0.025)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Tweet in Pre period FE	Yes	Yes	Yes	Yes	Yes	Yes
StockTwits controls$_{t-1 \ to \ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes
Factiva controls$_{t-1 \ to \ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes
N. observations	64,698,572	64,698,572	64,698,572	64,698,572	64,698,572	64,698,572
N. clusters (indiv.)	15900	15900	15900	15900	15900	15900
N. clusters (event)	652	652	652	652	652	652
R^2	0.127	0.127	0.127	0.127	0.127	0.127
Outcome mean $_{t-1 \ to \ t-3}$	2.40	2.40	2.40	2.40	2.40	2.40
Outcode SD $_{t-1 \ to \ t-3}$	15.30	15.30	15.30	15.30	15.30	15.30

The table presents estimates of equation 3, and includes estimates of interactions with individuals' personal characteristics. The dependent variable is $Deposit_{i,t}$ which equals 1 if individual i made a deposit into a cryptocurrency brokerage account on date t. Events$_e$ are defined at the day × celebrity level (a day may span multiple tweets from the same celebrity). The sample is at the *Event*, *Individual*, and *Date* level and spans the 3 days before the event to 3 days after. *EventDay* is an indicator variable marking the day when a celebrity tweet occurred and corresponds to $EventDay_{et_0}$ in equation 3. The pre-period (days t-1 through t-3) is the omitted time category. *Post* is an indicator for the post-period (day t+1 through t+3). Interactions with the corresponding indicator for missing characteristics (sex and credit score) are included but not reported in columns 2, 5 and 6. *Tweet in pre-period FE* is an indicator for whether there is another tweet in our sample occurring in the pre-period. *StockTwits controls* and *Factiva controls* indicate inclusion of three lags of the number of StockTwits posts and Factiva articles about crypto. *CS* stands for categorical credit score. The omitted categories for individual characteristics are Female, Income $\leq$ \$40k, Age$\leq$ 25, Credit Score: Poor. Standard errors (in parentheses) are separately clustered by individual$_i$ and event$_e$. *** 1%, ** 5%, * 10% significance level.

Table 7: Effect of Tweets on Cryptocurrency Deposits - By Coin

	(1)	(2)	(3)	(4)	(5)
EventDay	0.327***	0.278***	0.252***	0.270***	0.238***
	(0.074)	(0.055)	(0.056)	(0.054)	(0.062)
EventDay × BITCOIN	-0.095				
	(0.086)				
EventDay × ETHEREUM		-0.064			-0.028
		(0.116)			(0.120)
EventDay × DOGE			0.197*		0.199*
			(0.101)		(0.107)
EventDay × OTHERS				-0.014	0.028
				(0.145)	(0.149)
Post	0.174**	0.126***	0.086*	0.140***	0.098**
	(0.069)	(0.047)	(0.047)	(0.045)	(0.046)
Post × BITCOIN	-0.081				
	(0.068)				
Post × ETHEREUM		-0.034			-0.013
		(0.119)			(0.118)
Post × DOGE			0.238***		0.236***
			(0.087)		(0.087)
Post × OTHERS				-0.137	-0.085
				(0.116)	(0.117)
Event FE	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Tweet in Pre period FE	Yes	Yes	Yes	Yes	Yes
StockTwits controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes
Factiva controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes
N. observations	64,698,572	64,698,572	64,698,572	64,698,572	64,698,572
N. clusters (indiv.)	15900	15900	15900	15900	15900
N. clusters (event)	652	652	652	652	652
R2	0.127	0.127	0.127	0.127	0.127
Outcome mean$_{t-1\ to\ t-3}$	2.40	2.40	2.40	2.40	2.40
Outcode SD$_{t-1\ to\ t-3}$	15.30	15.30	15.30	15.30	15.30

The table presents estimates of equation 3, and includes estimates of interactions with indicators for the coin that is the focus of the celebrity tweet: BITCOIN, ETHEREUM, DOGE, and OTHERS. The dependent variable is $Deposit_{i,t}$ which equals 1 if individual i made a deposit into a cryptocurrency brokerage account on date t. Otherwise, the data and specification are identical to Table 6. In this table, *StockTwits* controls additionally include three lags of the number of StockTwits posts specific to a given coin. Standard errors (in parentheses) are separately clustered by individual$_i$ and event$_e$. *** 1%, ** 5%, * 10% significance level.

Table 8: Effect of Tweets on Investment Transactions - By Celebrity Type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Event	0.269***	0.272***	0.230***	0.278***	0.273***	0.307***	0.273***	0.234*
	(0.053)	(0.058)	(0.056)	(0.058)	(0.055)	(0.056)	(0.054)	(0.130)
EventDay × CELEBRITY		0.029						0.078
		(0.105)						(0.156)
EventDay × MUSIC			0.258**					0.265*
			(0.110)					(0.160)
EventDay × SPORTS				-0.040				0.025
				(0.100)				(0.153)
EventDay × INTERNET					-0.010			0.063
					(0.134)			(0.179)
EventDay × MONEY						-0.248**		-0.165
						(0.109)		(0.159)
EventDay × ELON MUSK							-0.042	0.000
							(0.134)	(0.000)
Post	0.121***	0.162***	0.090*	0.129**	0.092*	0.155***	0.119**	0.133
	(0.046)	(0.048)	(0.048)	(0.051)	(0.047)	(0.049)	(0.047)	(0.112)
Post × CELEBRITY		-0.155*						-0.115
		(0.084)						(0.130)
Post × MUSIC			0.209**					0.175
			(0.084)					(0.131)
Post × SPORTS				-0.037				-0.020
				(0.071)				(0.123)
Post × INTERNET					0.234**			0.216
					(0.091)			(0.137)
Post × MONEY						-0.217**		-0.189
						(0.086)		(0.132)
Post × ELON MUSK							0.019	0.000
							(0.110)	(0.000)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tweet in Pre period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StockTwits controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factiva controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Post variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. observations	64,698,572	64,698,572	64,698,572	64,698,572	64698572.000	64,698,572	64,698,572	64,698,572
N. clusters (indiv.)	15900	15900	15900	15900	15900	15900	15900	15900
N. clusters (event)	652	652	652	652	652	652	652	652
R2	0.127	0.127	0.127	0.127	0.127	0.127	0.127	0.127
Outcome mean$_{t-1\ to\ t-3}$	2.40	2.40	2.40	2.40	2.40	2.40	2.40	2.40
Outcode SD$_{t-1\ to\ t-3}$	15.30	15.30	15.30	15.30	15.30	15.30	15.30	15.30

The table presents estimates of equation 3, as well as estimates of interactions with indicators for celebrities' type. The dependent variable is $Deposit_{i,t}$ which equals 1 if individual i made a cryptocurrency deposit on date t. Otherwise, the data and specification are identical to Table 6. Standard errors (in parentheses) are separately clustered by individual$_i$ and event$_e$. *** 1%, ** 5%, * 10% significance level.

Table 9: Heterogeneity by Race and Political Affiliation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EventDay	0.252***	0.308***	0.249***	0.244***	0.265***	0.285***	0.242***
	(0.054)	(0.056)	(0.063)	(0.054)	(0.066)	(0.061)	(0.063)
EventDay × Latino	0.093						
	(0.084)						
EventDay × Black		-0.258***					
		(0.086)					
EventDay × White			0.039				
			(0.062)				
EventDay × Asian				0.391*			
				(0.201)			
EventDay × Democratic					0.009		
					(0.090)		
EventDay × Republican						-0.064	
						(0.104)	
EventDay × Independent							0.095
							(0.133)
Post	0.116**	0.124***	0.134***	0.111**	0.112**	0.140***	0.094**
	(0.046)	(0.047)	(0.048)	(0.046)	(0.050)	(0.046)	(0.047)
Post × Latino	0.024						
	(0.031)						
Post × Black		-0.016					
		(0.032)					
Post × White			-0.023				
			(0.022)				
Post × Asian				0.151**			
				(0.068)			
Post × Democratic					0.018		
					(0.032)		
Post × Republican						-0.076**	
						(0.037)	
Post × Independent							0.094*
							(0.053)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tweet in Pre period FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StockTwits controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Factiva controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Post variables	No	No	No	No	No	No	No
N. observations	64,217,123	64,217,123	64,217,123	64,217,123	64,598,164	64,598,164	64598164.000
N. clusters (indiv.)	652	652	652	652	652	652	652
N. clusters (event)	15783	15783	15783	15783	15878	15878	15878
R2	0.127	0.127	0.127	0.127	0.127	0.127	0.127
Outcome mean$_{t-1\ to\ t-3}$	2.4	2.4	2.4	2.4	2.4	2.4	2.4
Outcode SD$_{t-1\ to\ t-3}$	15.3	15.3	15.3	15.3	15.3	15.3	15.3

The table presents the estimates of the linear probability model outlined in equation 3 after adding interactions with location-level variables indicating either the county-level population shares of Latino, Black, White, and Asian populations, or the share of voters by political party registration as of October 2020. The dependent variable is $Deposit_{i,t}$ which equals 1 if individual i made a deposit into a cryptocurrency brokerage account on date t. Otherwise, the data and specification are identical to Table 6. Standard errors (in parentheses) are separately clustered by individual$_i$ and event$_e$. *** 1%, ** 5%, * 10% significance level.

Table 10: Extensive margin model

	All Investments		Extensive Margin		Intensive Margin	
	(1)	(2)	(3)	(4)	(5)	(6)
EventDay-2		0.045		0.006		0.039
		(0.043)		(0.009)		(0.036)
EventDay-1		0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)
EventDay	0.269***	0.288***	0.044***	0.044***	0.225***	0.244***
	(0.053)	(0.058)	(0.012)	(0.013)	(0.045)	(0.049)
EventDay+1		0.079		0.020		0.059
		(0.057)		(0.013)		(0.047)
EventDay+2		0.196***		0.026**		0.170***
		(0.054)		(0.013)		(0.044)
EventDay+3		0.144**		0.012		0.132***
		(0.060)		(0.015)		(0.049)
Post	0.121***		0.019*		0.101***	
	(0.046)		(0.012)		(0.037)	
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Tweet in Pre period FE	Yes	Yes	Yes	Yes	Yes	Yes
StockTwits controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes
Factiva controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes
N. observations	64,698,572	64,698,572	64,698,572	64,698,572	64,698,572	64,698,572
N. clusters (indiv.)	15900	15900	15900	15900	15900	15900
N. clusters (event)	652	652	652	652	652	652
R2	0.127	0.127	0.005	0.005	0.139	0.139
Outcome mean	2.4	2.4	0.27	0.27	2.13	2.13
Outcode SD	15.3	15.3	5.16	5.16	14.45	14.45

This table presents the results of event study regressions split into extensive and intensive margins. The dependent variable is $Deposit_{i,t}$ which equals 1 if a user i made a deposit into a cryptocurrency brokerage account on date t. Panel *All Investments* includes all investment transactions, panel *Extensive Margin* only includes first crypto investments made by users and panel *Intensive Margin* includes all investments with the exception of first transactions. Relative to equation 3 this model explicitly estimates the effect at different days relative to a tweet. Relative time dummy k days after the tweet is denoted by *EventDay+k*. *EventDay-1* is the omitted category. Otherwise, the definitions and data are identical to Table 6. Standard errors (in parentheses) are separately clustered by individual$_i$ and event$_e$. *** 1%, ** 5%, * 10% significance level.

Online Appendix

Celebrity Persuasion

Matteo Benetton, William Mullins, Marina Niessner and Jan Toczynski

Figure A1: Sample Celebrity Tweets

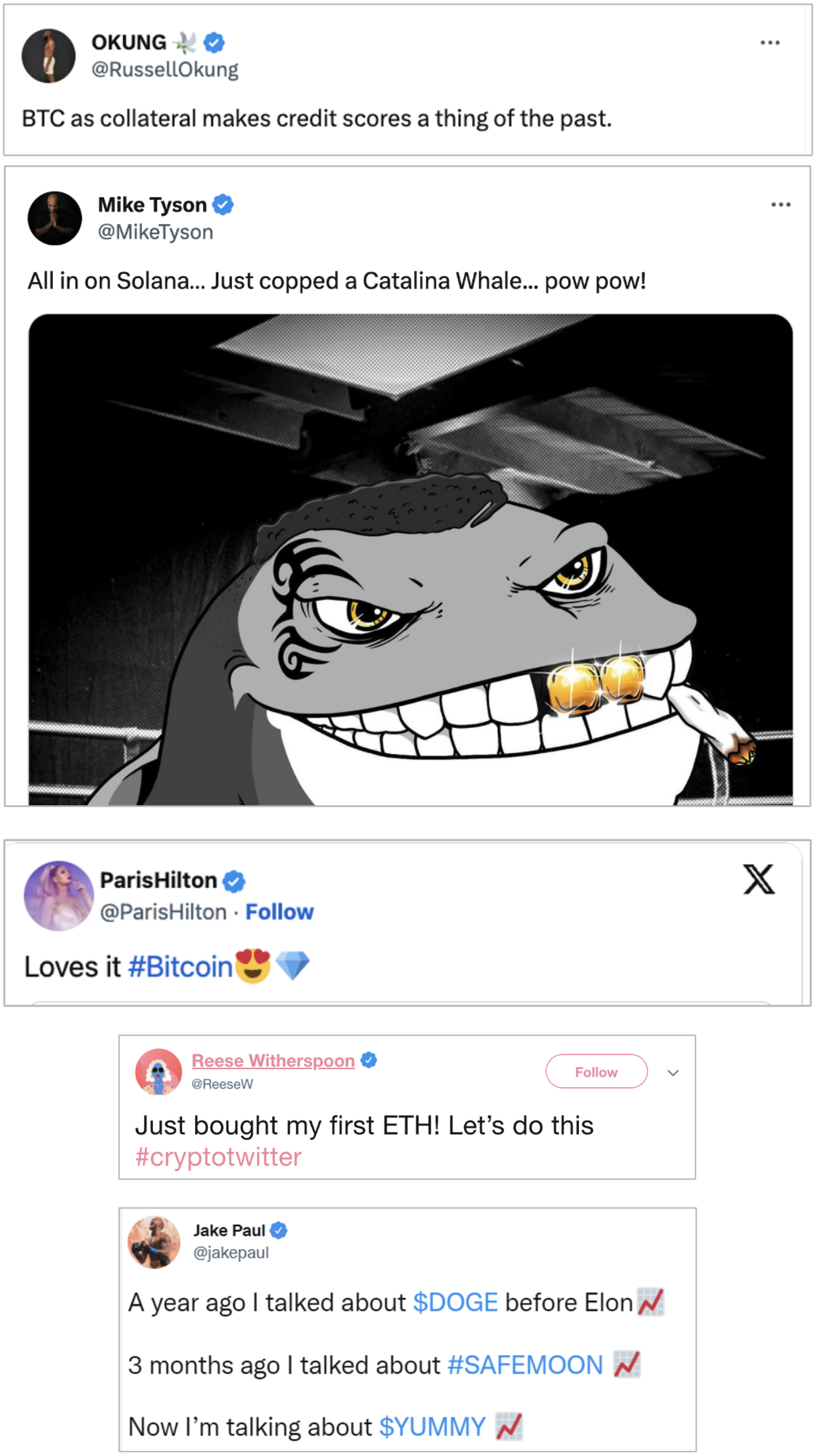
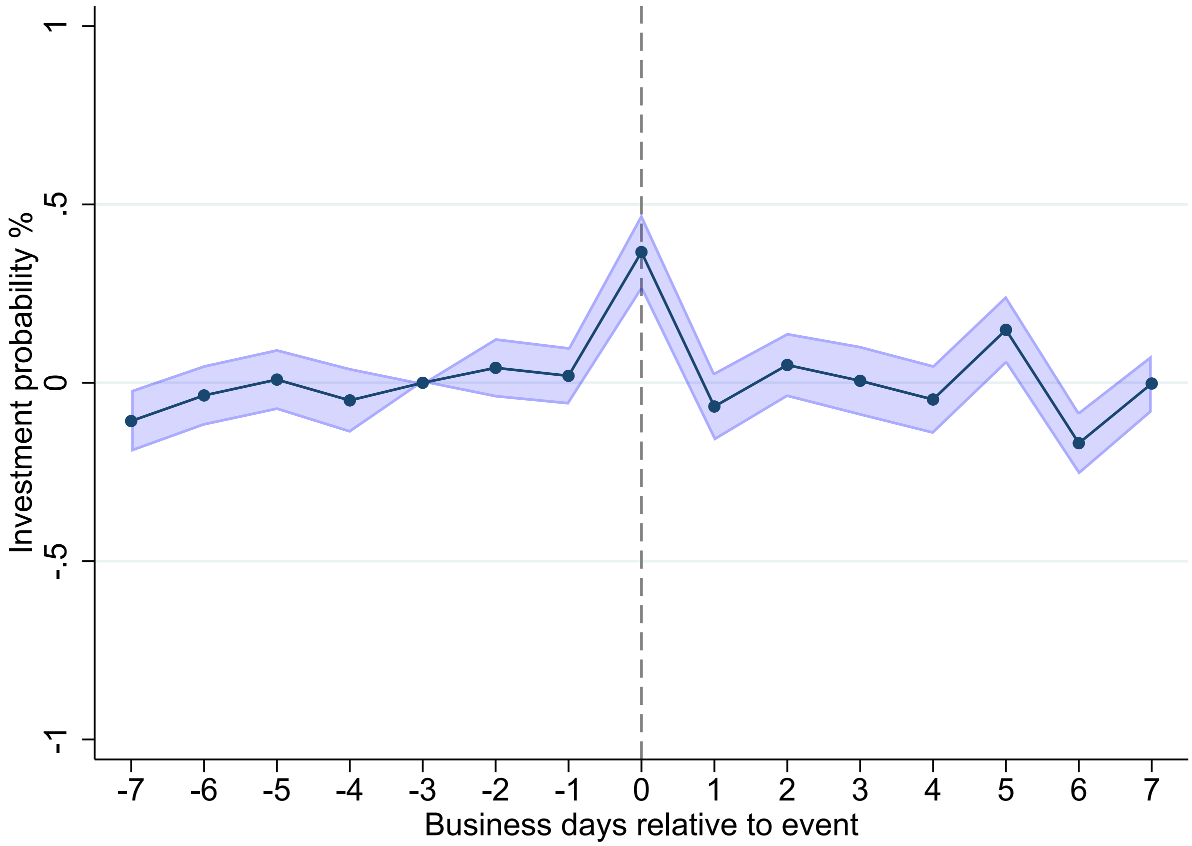


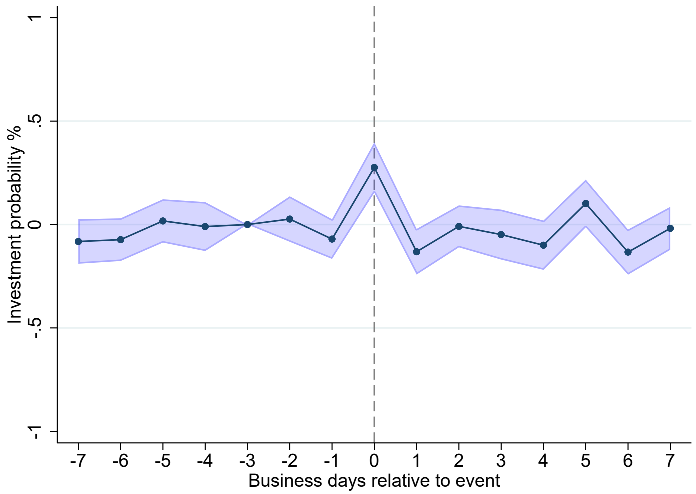
Figure A2: Dynamic investment response - control for post-event Tweets



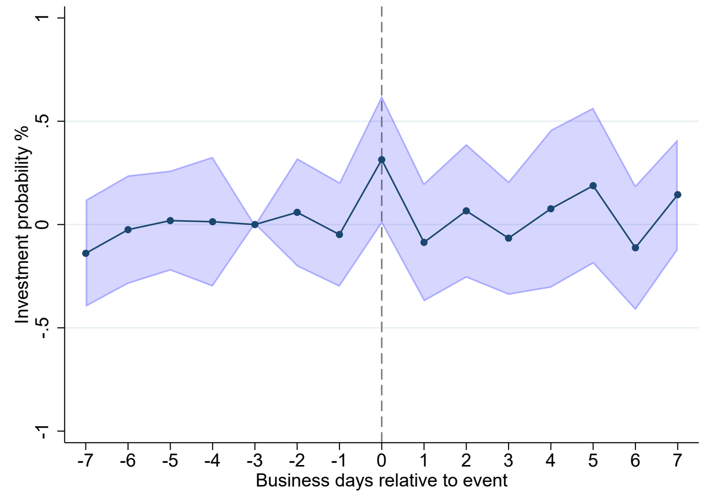
Note: This figure plots estimated treatment effect coefficients from equation 2 after additionally controlling for celebrity tweets in the post-event period ($\phi_{post}\mathbb{1}_{et}^{Post\ tweet}$). The dependent variable is an investment indicator. Day -3 is the reference category. 95% confidence intervals double clustered at the user and day level.

Figure A3: Effects by coin - control for post-event Tweets

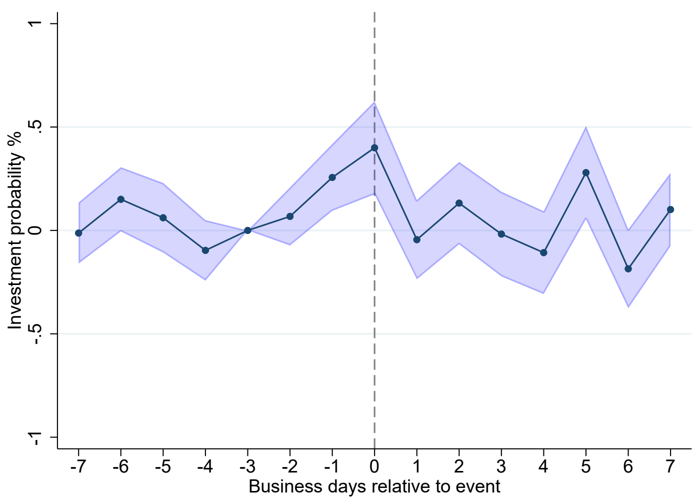
(a) Bitcoin



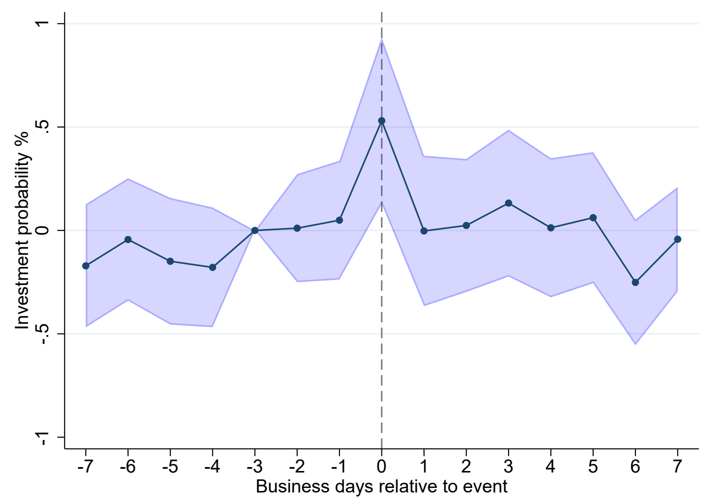
(b) Ether



(c) DogeCoin

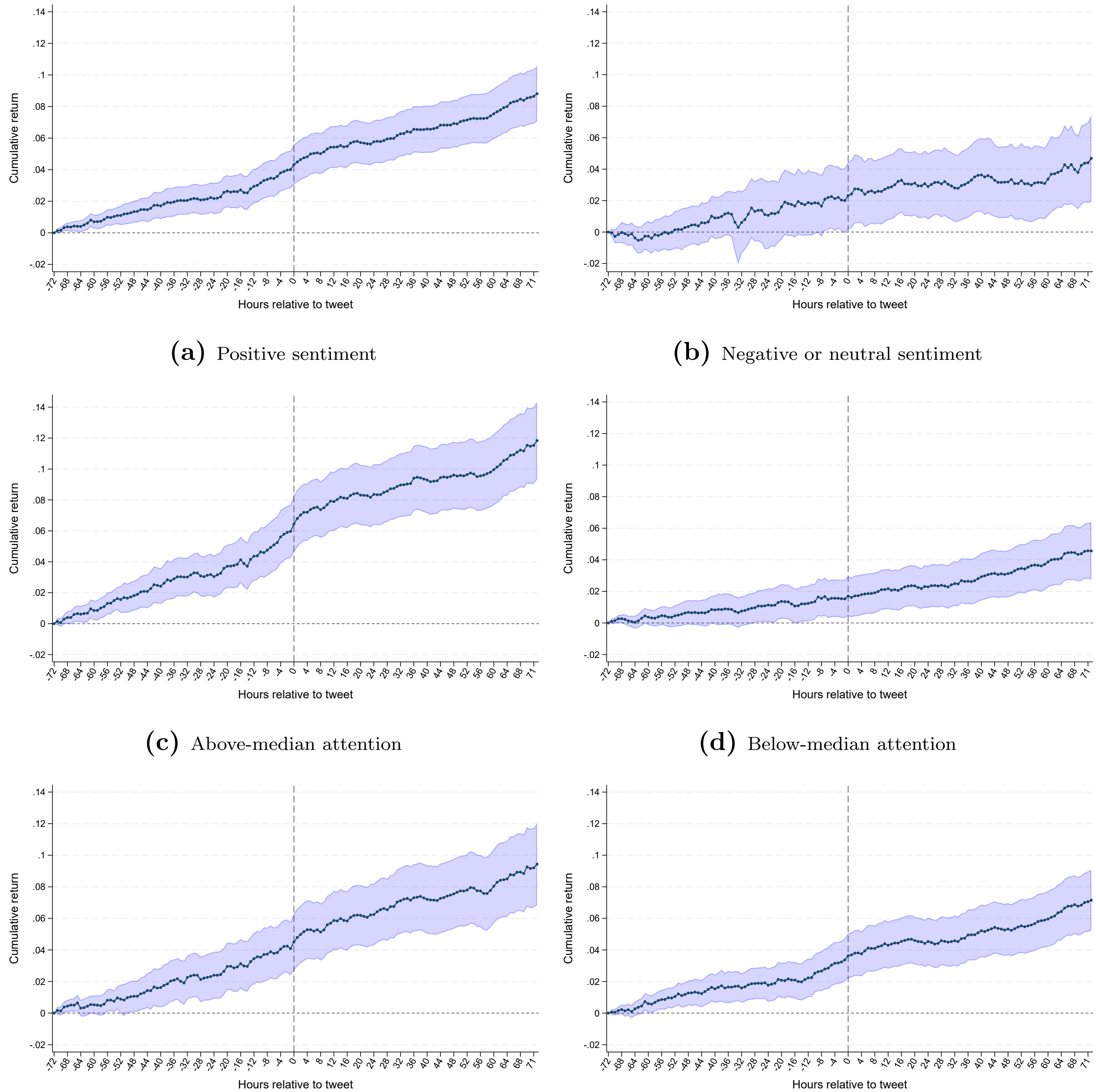


(d) Other coins



Note: This figure plots estimated treatment effect coefficients from equation 2 after additionally controlling for celebrity tweets in the post-event period ($\phi_{post}\mathbb{1}_{et}^{Post\ tweet}$). The dependent variable is an investment indicator. Subfigure (a) plots the results for Bitcoin, (b) for Ethereum, (c) for Dogecoin, and (d) for the other coins in our sample (Ripple, Cardono, Polygon, and Shiba Inu). Day -3 is the reference category. 95% confidence intervals double clustered at the user and day level.

Figure A4: Heterogeneity analysis for Cumulative Returns by tweet characteristics



(a) Positive sentiment

(b) Negative or neutral sentiment

(c) Above-median attention

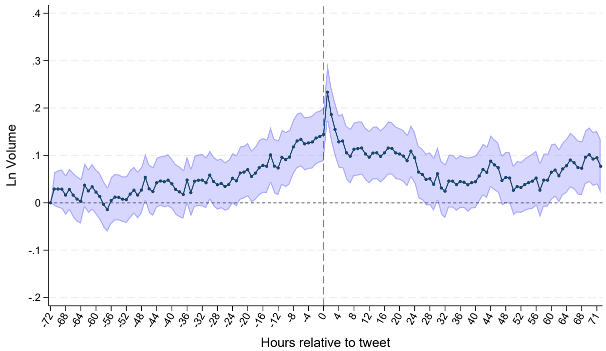
(d) Below-median attention

(e) Above-median follower count

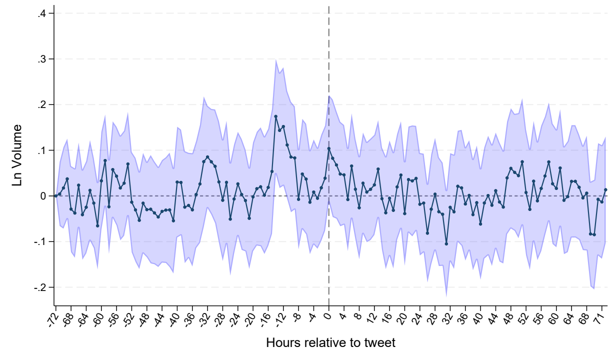
(f) Below-median follower count

Note: This figure reproduces the analysis in Figure 7 but separates the sample by sentiment, attention and follower count. The first row separates the sample into focal tweets expressing (i) positive sentiment (panel a) and (ii) neutral or negative sentiment (panel b). Around 85% of tweets in our sample express positive sentiment, while 6% express negative sentiment; there are not enough negative tweets to separate neutral tweets from negative ones. The second row splits tweets into above- and below-median attention, defined as likes + retweets + quotes + replies (panels c and d, respectively). The third row splits tweets by above- and below-median follower counts (panels e and f). 95% confidence intervals.

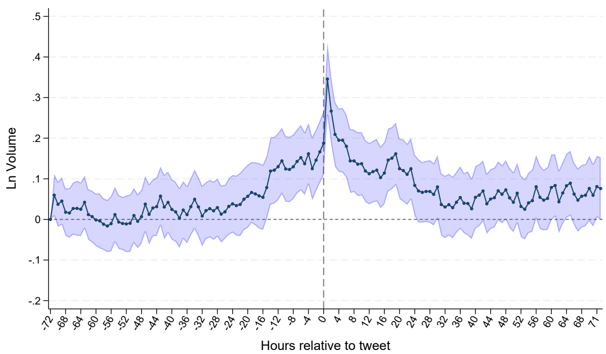
Figure A5: Heterogeneity analysis for Trading Volume by tweet characteristics



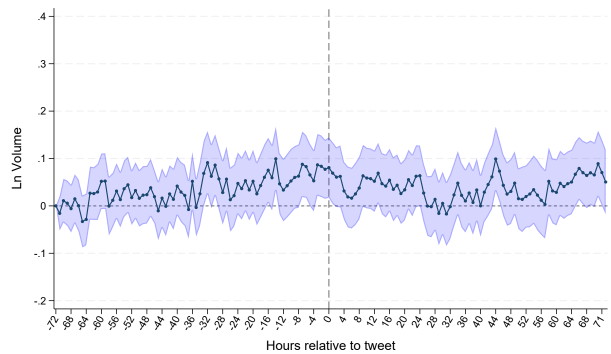
(a) Positive sentiment



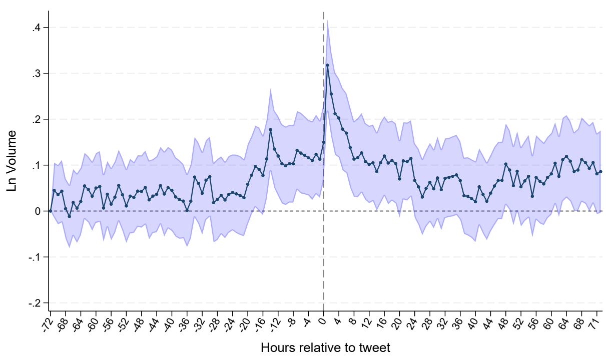
(b) Negative or neutral sentiment



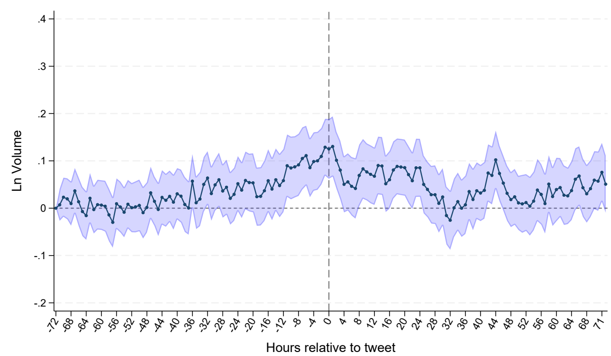
(c) Above-median attention



(d) Below-median attention



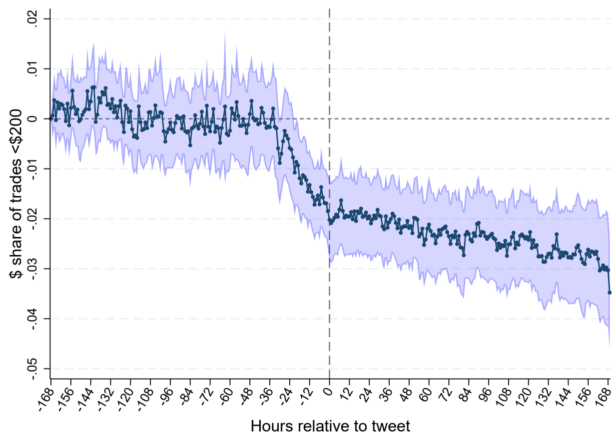
(e) Above-median follower count



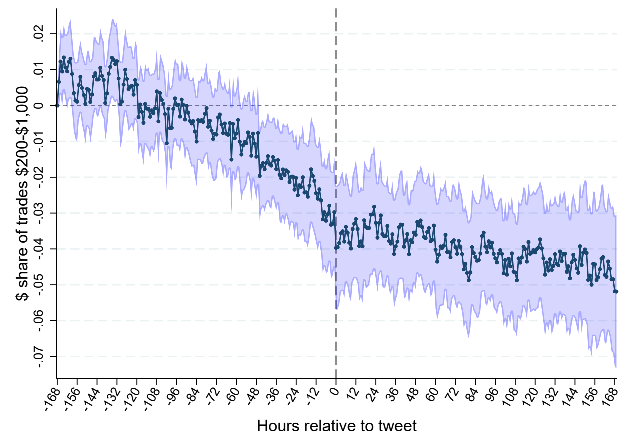
(f) Below-median follower count

Note: This figure reproduces the analysis in Figure 8 panel a, but separates the sample by sentiment, attention and follower count. The first row separates the sample into focal tweets expressing (i) positive sentiment (panel a) and (ii) neutral or negative sentiment (panel b). Around 85% of tweets in our sample express positive sentiment, while 6% express negative sentiment; there are not enough negative tweets to separate neutral tweets from negative ones. The second row splits tweets into above- and below-median attention, defined as likes + retweets + quotes + replies (panels c and d, respectively). The third row splits tweets by above- and below-median follower counts (panels e and f). 95% confidence intervals.

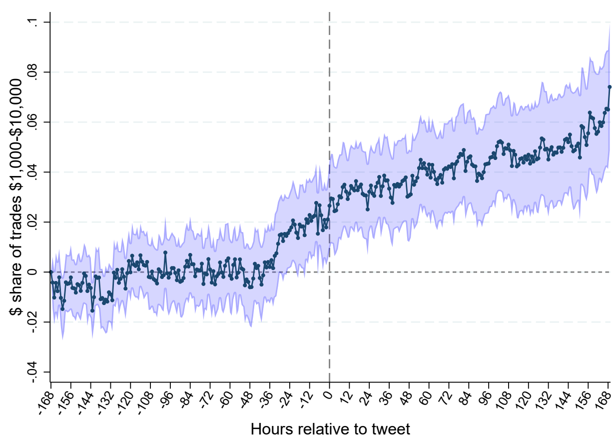
Figure A6: DogeCoin trades by trade size excluding Elon Musk events



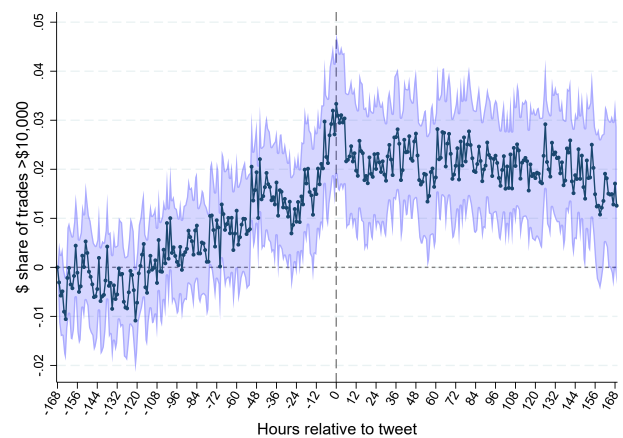
(a) Trades $\leq$ \$200



(b) \$200 $<$ Trades $\leq$ \$1,000



(c) \$1,000 $<$ Trades $\leq$ \$10,000



(d) Trades $>$ \$10,000

Note: This figure reproduces the analysis in Figure 10, for the 128 focal tweets (events) in the sample that are *not* by Elon Musk.

Table A1: Celebrities and Tweets

USERNAME	NAME	TWEETS	FOLLOWERS	GENDER	RACE	TYPE
RussellOkung	Russel Okung	314	261,334	Male	Black	Sports
KEEMSTAR	KEEM	188	2,600,000	Male	White	Internet
mcuban	Mark Cuban	177	8,850,122	Male	White	Shark Tank
elonmusk	Elon Musk	132	136,797,868	Male	White	Elon Musk
KaiGreene	Kai Greene	115	318,813	Male	Black	Celebrity
stoolpresidente	Dave Portnoy	96	2,905,156	Male	White	Celebrity
genesimmons	Gene Simmons	74	1,038,518	Male	White	Musician
souljaboy	Soulja Boy	58	5,489,716	Male	Black	Musician
kevinolearytv	Kevin Oleary	47	984,522	Male	White	Shark Tank
MattBarkley	Matt Barkley	38	114,958	Male	White	Sports
mattjames919	Matt James	22	77,354	Male	Black	Celebrity
nickcarter	Nick Carter	18	693,931	Male	White	Musician
MKBHD	Marques Brownlee	17	6,032,929	Male	Black	Internet
aplusk	Ashton Kutcher	11	16,875,977	Male	White	Celebrity
jakepaul	Jake Paul	10	4,599,379	Male	White	Internet
miakhalifa	Mia Khalifa	10	5,443,443	Female	White	Celebrity
lilyachty	Lil Yachty	9	5,418,662	Male	Black	Musician
MrBeast	Mr Beast	6	19,878,971	Male	White	Internet
marcdamelio	Marc Damelio	5	662,785	Male	White	Internet
MikeTyson	Mike Tyson	5	5,909,893	Male	Black	Sports
ParisHilton	Paris Hilton	5	16,813,885	Female	White	Celebrity
Akon	Akon	4	6,104,181	Male	Black	Musician
andre	Andre Iguodalaÿ	4	1,358,004	Male	Black	Sports
LilNasX	Lil Nas	4	8,056,152	Male	Black	Musician
MeekMill	MeekMill	4	11,465,404	Male	Black	Musician
OfficialMelB	Mel B	4	965,500	Female	Black	Celebrity
saquon	Saquon Barkley	4	507,123	Male	Black	Sports
deadmau5	deadmau5	4	3,295,006	Male	White	Musician
ANGELAWHITE	Angela White	3	2,686,157	Female	White	Celebrity
AB84	Antonio Brown	2	1,637,146	Male	White	Sports
FloydMayweather	Floyd Mayweather	2	7,754,818	Male	Black	Sports
SnoopDogg	Snoop Dogg	2	20,932,537	Male	Black	Musician
steveaoki	steveaoki	2	8,054,849	Male	Asian	Musician
AaronRodgers12	Aaron Rodgers	1	4,597,336	Male	Black	Sports
CadeCunningham_	Cade Cunningham	1	103,593	Male	Black	Sports
GuyFieri	Guy Fieri	1	3,529,380	Male	White	Celebrity
GwynethPaltrow	Gwyneth Paltrow	1	2,705,301	Female	White	Celebrity
FINALLEVEL	ICE T	1	1,944,173	Male	Black	Musician
JHarden13	James Harden	1	7,765,688	Male	Black	Sports
sc	Jay-Z	1	3,048,714	Male	Black	Musician
KlayThompson	Klay Thompson	1	1,847,493	Male	White	Sports
lindsaylohan	Lindsay Lohan	1	8,119,617	Female	White	Celebrity
iamlorengray	Loren Gray	1	1,580,336	Female	White	Internet
Madonna	Madonna	1	2,848,486	Female	White	Musician
Maisie_Williams	Maisie Williams	1	2,479,874	Female	White	Celebrity
obj	Odell Beckham Jr	1	4,411,279	Male	Black	Sports
paulpierce34	Paul Pierce	1	4,022,288	Male	Black	Sports
Pharrell	Pharrell	1	10,455,064	Male	Black	Musician
thegame	The Game	1	1,117,160	Male	Black	Musician
TomBrady	Tom Brady	1	3,073,808	Male	White	Sports
ThisIsUD	Udonis Haslem	1	395,430	Male	Black	Sports
diplo	diplo	1	2,409,900	Male	White	Musician

Table A2: Words included in RegEx search

Symbol	Alt Name 1	Alt Name 2
ada	cardano	
ape	apecoin	
atom	cosmos	
ava	travala	
avax	avalanche	
axs	axie infinity	
bch	bitcoin cash	
bch	bitcoin cash	
bnb	bnb	
btc	bitcoin	
busd	binance usd	
cob	cobinhood	
cream	cream finance	C.R.E.A.M.
cro	cronos	
crypto	crypto	
dai	dai	
doge	dogecoin	dogcoin
dot	polkadot	
emax	ethereumMax	
etc	Ethereum Classic	
eth	ethereum	ether
floki	floki	
ftx	ftx	
ldn	lydian	lydiancoin
leo	unus sed leo	
link	chainlink	
ltc	litecoin	
luna	terra	
lunc	terra classic	
matic	polygon	
near	near protocol	
nft	nft	
okb	okb	
pot	potcoin	
safemoon	sfm	
shib	shiba inu	shibarmy
sol	solana	
stx	stacks	
ton	toncoin	
trx	tron	
uni	uniswap	
usdc	usd coin	
usdt	tether	
wbtc	wrapped bitcoin	
xlm	stellar	
xmr	monero	
xrp	ripple	
yummy	yummy coin	
psg	Paris Saint-Germain	

Table A3: Identification of crypto flows

This table outlines keywords we used to identify cryptocurrency flows in the transaction data.

Type	**Keyword dictionary**
Crypto	{"coinbase", "voyager", "blockfi", "uphold", "kraken", "etoro", "crypto.com" "crypto com" "binance" "holdnaut" "coinmama", "ftxus", "blockfolio", "cryptohub", "crypto hub", "gemini.co", "okcoin", "bittrex", "cexio", "bitstamp", "changelly", "polonix", " okx", "bitfinex", "bybit", "bitflyer", "kucoin", "bitmart", "upbit", "bitrue", "crypto hu", "bitcoin", "cardano", "ethereum", "doge", "shiba inu", "litecoin", "pokladot"}

Table A4: The Role of Opinions: Heterogeneity

Standard errors are clustered at the firm and month×year level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***

	Gender		Age		Ethnicity		Education		Income (K$)		Location		Job type	
	Female	Male	>45	<45	White	Non-white	College+	No college	>50	<50	Other	Urban	Other	Self-employed, homemaker, unemployed
Kim Kardashian: Negative	-0.13*	-0.10	-0.06	-0.11	-0.15**	-0.01	-0.10	-0.05	-0.12	-0.01	-0.09*	-0.07	-0.13**	0.03
	(0.07)	(0.08)	(0.06)	(0.07)	(0.07)	(0.08)	(0.10)	(0.06)	(0.08)	(0.06)	(0.05)	(0.11)	(0.06)	(0.10)
Kim Kardashian: Positive	0.02	0.10	0.01	0.18**	-0.00	0.20*	0.13	0.11*	0.10	0.16**	0.10	0.09	0.08	0.23**
	(0.08)	(0.09)	(0.07)	(0.08)	(0.08)	(0.10)	(0.11)	(0.07)	(0.09)	(0.08)	(0.07)	(0.11)	(0.08)	(0.10)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Opinion asset	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Y	0.08	0.26	0.06	0.26	0.20	0.20	0.27	0.11	0.25	0.11	0.11	0.32	0.21	0.15
SD Y	0.28	0.44	0.24	0.44	0.40	0.40	0.45	0.32	0.43	0.32	0.31	0.47	0.41	0.35
R2	0.23	0.30	0.28	0.28	0.30	0.48	0.38	0.19	0.32	0.29	0.19	0.34	0.28	0.39
Obs.	156	243	132	267	259	108	201	198	238	161	235	164	296	103

Table A5: Effect of Tweets on Cryptocurrency Deposits

	(1)	(2)	(3)	(4)	(5)	(6)
EventDay	0.1803***	0.0477	0.0556	-0.0605	0.1147**	-0.3065***
	(0.0491)	(0.0511)	(0.0491)	(0.0588)	(0.0555)	(0.0774)
EventDay × Male		0.2272***				0.2415***
		(0.0421)				(0.0427)
EventDay × Income>40k			0.1227***			0.0505
			(0.0363)			(0.0358)
EventDay × Income>80k			0.2866***			0.1386***
			(0.0552)			(0.0527)
EventDay × Age>25				0.2043***		0.1764***
				(0.0454)		(0.0457)
EventDay × Age>35				0.3675***		0.3244***
				(0.0598)		(0.0599)
EventDay × CS: Average					0.0842	0.0822
					(0.0519)	(0.0520)
EventDay × CS: Good					0.0909	0.0906
					(0.0593)	(0.0592)
EventDay × CS: Excellent					0.2378***	0.2100***
					(0.0635)	(0.0637)
Post	0.0598	0.0594	0.0410	0.0406	0.0376	0.0139
	(0.0383)	(0.0363)	(0.0364)	(0.0386)	(0.0382)	(0.0393)
Post × Male		0.0082				0.0069
		(0.0148)				(0.0147)
Post × Income>40k			0.0210			0.0155
			(0.0129)			(0.0129)
Post × Income>80k			0.0398*			0.0252
			(0.0205)			(0.0186)
Post × Age>25				0.0209		0.0106
				(0.0174)		(0.0175)
Post × Age>35				0.0217		0.0059
				(0.0213)		(0.0214)
Post × CS: Average					0.0325*	0.0306*
					(0.0171)	(0.0168)
Post × CS: Good					0.0319	0.0292
					(0.0214)	(0.0210)
Post × CS: Excellent					0.0673**	0.0619**
					(0.0262)	(0.0247)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Tweet in Pre period FE	Yes	Yes	Yes	Yes	Yes	Yes
StockTwits controls$_{t-0\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes
Factiva controls$_{t-0\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes
N. observations	64,698,572	64,698,572	64,698,572	64,698,572	64,698,572	64,698,572
N. clusters (indiv.)	15900	15900	15900	15900	15900	15900
N. clusters (event)	652	652	652	652	652	652
R2	0.127	0.127	0.127	0.127	0.127	0.127
Outcome mean$_{t-1\ to\ t-3}$	2.40	2.40	2.40	2.40	2.40	2.40
Outcode SD$_{t-1\ to\ t-3}$	15.30	15.30	15.30	15.30	15.30	15.30

The table presents estimates of equation 3 for interactions of individual characteristics with the event on day zero (i.e., the day a celebrity tweets). Events are defined at the day × celebrity level. The dependent variable is $Deposit_{i,t}$ which equals 1 if a user i made a cryptocurrency deposit on date t. The sample is at the *Event*, *Individual*, and *Date* level and spans the 3 days before the event to 3 days after. *EventDay* is an indicator variable marking the day when a celebrity tweet occurred and corresponds to $EventDay_{et_0}$ in equation 3. The pre-period (i.e., days t-0 through t-3) is the omitted time category. *Post* indicates the indicator variable for the post-period (i.e., day t+1 through t+3, equivalent to $Post_{et}$ in equation 3). *Tweet in pre-period FE* is an indicator for whether there is another tweet in our sample occurring in the pre-period. *StockTwits controls* and *Factiva controls* indicate inclusion of three lags of the number of StockTwits posts and Factiva articles about crypto, respectively. The omitted categories for individual characteristics are Female, Income $\leq$ \$40k, Age$\leq$ 25, Credit Score: Poor. *CS* stands for categorical credit score. *N/A* is an indicator for missing information. Standard errors are clustered at the individual and event level and reported in parentheses. *** 1%, ** 5%, * 10% significance level.

Table A6: Effect of Tweets on Withdrawal Transactions

	(1)	(2)	(3)	(4)	(5)	(6)
EventDay	0.0247***	-0.0217**	0.0296***	0.0424**	0.0460***	0.0186
	(0.0082)	(0.0097)	(0.0104)	(0.0175)	(0.0126)	(0.0211)
EventDay × Male		0.0605***				0.0594***
		(0.0108)				(0.0107)
EventDay × Income>40k			-0.0064			-0.0014
			(0.0101)			(0.0105)
EventDay × Income>80k			-0.0088			0.0086
			(0.0114)			(0.0123)
EventDay × Age>25				-0.0167		-0.0098
				(0.0160)		(0.0163)
EventDay × Age>35				-0.0242		-0.0149
				(0.0174)		(0.0182)
EventDay × CS: Average					-0.0126	-0.0137
					(0.0151)	(0.0152)
EventDay × CS: Good					-0.0778***	-0.0789***
					(0.0140)	(0.0142)
EventDay × CS: Excellent					-0.0613***	-0.0651***
					(0.0140)	(0.0145)
Post	0.0119**	0.0030	0.0099	-0.0011	0.0164**	-0.0071
	(0.0059)	(0.0064)	(0.0064)	(0.0091)	(0.0071)	(0.0102)
Post × Male		0.0127***				0.0135***
		(0.0049)				(0.0049)
Post × Income>40k			0.0027			0.0002
			(0.0047)			(0.0051)
Post × Income>80k			0.0034			0.0007
			(0.0053)			(0.0058)
Post × Age>25				0.0137*		0.0145*
				(0.0080)		(0.0082)
Post × Age>35				0.0152*		0.0168**
				(0.0081)		(0.0085)
Post × CS: Average					-0.0051	-0.0047
					(0.0065)	(0.0066)
Post × CS: Good					-0.0088	-0.0081
					(0.0064)	(0.0066)
Post × CS: Excellent					-0.0076	-0.0077
					(0.0061)	(0.0065)
Event FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Tweet in Pre period FE	Yes	Yes	Yes	Yes	Yes	Yes
StockTwits controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes
Factiva controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes	Yes
N. observations	64,698,572	64,698,572	64,698,572	64,698,572	64,698,572	64,698,572
N. clusters (indiv.)	15900	15900	15900	15900	15900	15900
N. clusters (event)	652	652	652	652	652	652
R2	0.039	0.039	0.039	0.039	0.039	0.039
Outcome mean$_{t-1\ to\ t-3}$	0.37	0.37	0.37	0.37	0.37	0.37
Outcome SD$_{t-1\ to\ t-3}$	6.08	6.08	6.08	6.08	6.08	6.08

The table presents estimates of equation 3 for interactions of individual characteristics with the event on day zero (i.e., the day a celebrity tweets). Events are defined at the day × celebrity level. The dependent variable is $Withdrawal_{i,t}$ which equals 1 if a user i made a withdrawal from a cryptocurrency brokerage on date t. The sample is at the *Event*, *Individual*, and *Date* level and spans the 3 days before the event to 3 days after. *EventDay* is an indicator variable marking the day when a celebrity tweet occurred and corresponds to $EventDay_{et_0}$ in equation 3. The pre-period (i.e., days t-0 through t-3) is the omitted time category. *Post* indicates the indicator variable for the post-period (i.e., day t+1 through t+3, equivalent to $Post_{et}$ in equation 3). *Tweet in pre-period FE* is an indicator for whether there is another tweet in our sample occurring in the pre-period. *StockTwits controls* and *Factiva controls* indicate inclusion of three lags of the number of StockTwits posts and Factiva articles about crypto, respectively. The omitted categories for individual characteristics are Female, Income $\leq$ \$40k, Age$\leq$ 25, Credit Score: Poor. *CS* stands for categorical credit score. *N/A* is an indicator for missing information. Standard errors are clustered at the individual and event level and reported in parentheses. *** 1%, ** 5%, * 10% significance level.

Table A7: Effect of Tweets on Cryptocurrency Deposits

	(1)	(2)	(3)	(4)	(5)
EventDay	0.284***	0.206	0.268***	0.235**	0.208
	(0.054)	(0.129)	(0.102)	(0.092)	(0.205)
EventDay $\times LogLikes$		0.011			0.030
		(0.016)			(0.069)
EventDay $\times LogReplies$			0.003		-0.048
			(0.017)		(0.047)
EventDay $\times LogRetweet$				0.010	0.022
				(0.015)	(0.066)
Post	0.137***	0.017	0.102	0.061	0.021
	(0.047)	(0.098)	(0.081)	(0.067)	(0.146)
Post $\times LogLikes$		0.016			0.038
		(0.013)			(0.043)
Post $\times LogReplies$			0.007		-0.059
			(0.015)		(0.036)
Post $\times LogRetweets$				0.015	0.028
				(0.012)	(0.045)
Event FE	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Tweet in Pre period FE	Yes	Yes	Yes	Yes	Yes
StockTwits controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes
Factiva controls$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes
Past returns$_{t-1\ to\ t-3}$	Yes	Yes	Yes	Yes	Yes
Post variables	Yes	No	No	No	No
N. observations	63110695.0000	63110695.0000	63110695.0000	63110695.0000	63110695.0000
N. clusters (indiv.)	15900	652	652	652	15900
N. clusters (event)	652	15900	15900	15900	652
R2	0.1267	0.1267	0.1267	0.1267	0.1267
Outcome mean	2.41	2.41	2.41	2.41	2.41
Outcode SD	15.33	15.33	15.33	15.33	15.33

Standard errors in parentheses
* p¡.10, ** p¡.05, *** p¡.01

The table presents estimates of equation 3 for interactions of individual characteristics with the event on day zero (i.e., the day a celebrity tweets). Events are defined at the day × celebrity level. The dependent variable is $Deposit_{i,t}$ which equals 1 if a user i made a cryptocurrency deposit on date t. The sample is at the *Event*, *Individual*, and *Date* level and spans the 3 days before the event to 3 days after. *EventDay* is an indicator variable marking the day when a celebrity tweet occurred and corresponds to $EventDay_{et_0}$ in equation 3. The pre-period (i.e., days t-0 through t-3) is the omitted time category. *Post* indicates the indicator variable for the post-period (i.e., day t+1 through t+3, equivalent to $Post_{et}$ in equation 3). *Tweet in pre-period FE* is an indicator for whether there is another tweet in our sample occurring in the pre-period. *StockTwits controls* and *Factiva controls* indicate inclusion of three lags of the number of StockTwits posts and Factiva articles about crypto, respectively. The omitted categories for individual characteristics are Female, Income $\leq \$40k$, Age$\leq$ 25, Credit Score: Poor. *CS* stands for categorical credit score. *N/A* is an indicator for missing information. Standard errors are clustered at the individual and event level and reported in parentheses. *** 1%, ** 5%, * 10% significance level.