Celebrity Influencers: *This is not Financial Advice*[*]

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Abstract

As younger adults look to social media for news and investment guidance about cryptocurrencies, a new group of 'financial advisors' has emerged with an unprecedented reach – celebrity influencers. In this paper we combine survey responses and transaction-level data with real-life celebrities' crypto-related Twitter posts to study how celebrity endorsements shape households' financial decisions. We find that a celebrity tweet is associated with a 16% higher probability that an individual invests in cryptocurrencies, with stronger effects for men, wealthier, and older investors. We also find that aggregate market trading volume in a given coin increases by 10% on the day of the celebrity tweet and stays elevated for the following two days, while returns exhibit a 3% spike with no reversal over the following week. We conclude by showing that investors would have been better off buying Bitcoin or Ethereum than the coin mentioned in the celebrity tweet.

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

JEL Codes: XX, YY

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1. Introduction

Celebrities have been endorsing products for over two hundred years (NPR, 2012), but social media's reach and immediacy has led to widespread and 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), celebrities have begun to endorse financial products, especially those related to the largely unregulated cryptocurrency sector, with ambiguous impacts on investors (Bloomberg News, 2022). For example, Kim Kardashian recently settled an SEC lawsuit after promoting cryptocurrency Ethereum Max (EMAX) 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, we examine the advice provided by this new class of 'financial advisors', their effect on households' investments and financial markets, and the characteristics of people who follow their advice.

Most prior literature on financial advice focuses on the stock market and on certified financial advisors, since a large fraction of individual investors turn to these professionals for investment guidance.[1] However, cryptocurrency markets have grown rapidly over the past decade: more than 1-in-10 Americans own cryptocurrencies (Weber et al. (2023)) - especially among communities with low participation and trust in traditional financial markets (such as minorities in the U.S.), due to their purported ability to *democratize finance* and allow people to build wealth without interacting with the traditional financial system (Woelfel, 2021). Due to lack of expertise about a new asset class or simple skepticism, certified professional advisors - who play an important role in the stock market - have a substantially smaller role in the crypto sector.[2] The combination of a relative lack of *supply* of advice by professionals and an increasing *demand* of advice by retail investors has opened the door to new providers of financial advice: real-world celebrities - like Kim Kardashian - who have millions of followers on social media and little to no knowledge about the financial products

[1] https://www.riaintel.com/article/2buzyinjbu0qt7sc9xxc0/practice-management/are-social-media-influencers-out-influencing-financial-advisors

[2] 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).

they endorse.[3]

To study the celebrity financial advice ecosystem we make use of several data sources. We start by using Morning Consult microdata from a survey conducted around the time of the Kim Kardashian lawsuit. 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. To further explore the quantitative importance of celebrity finfluencers' financial advice and the types of investors who act on it, we utilize all cryptocurrency-related tweets by the top 75 real-world celebrities turned crypto influencers, together with transaction-level data gathered by a U.S. fintech company.[4] We show that celebrity tweets are associated with a 16% increase in the probability of investing in crypto, driven by men and by older users. We also find that individuals living in areas with a higher Black share are *less* likely to act on celebrity tweets, while those in more Asian areas are *more* likely. We then use a difference in differences design to explore the effects of a celebrity tweet on the market as a whole. The tweets in our data are associated with a 3% spike in returns on day 0, with no reversal over the following week. Moreover, trading volume increases by 10% on the day of the tweet and stays elevated for the following two days, consistent with substantial market impact. Finally, we compare the quality of celebrity crypto advice to the advice of more traditional *finfluencers* - in particular, those with the most followers on the investor social media platform StockTwits. We find that, while the sentiment of finfluencer messages does not forecast future crypto returns, the number of messages has a positive association with future returns and trading volume for smaller coins.

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 lawsuit against Kim Kardashian. This 2,200 respondent survey asked detailed questions about their investments, demographic characteristics, opinions about celebrity influencers, and social media usage. We find that the respondents who invest

[3]Another growing category of advisors leveraging social media are the so-called *finfluencers*, some of whom are also professional investors or advisors (e.g., Cookson and Niessner, 2020).

[4]The coins in our tweet-based sample are Bitcoin (BTC), Ether (ETH), Doge (DOGE), Ripple (XRP), Cardano (ADA), Solana (SOL), Tron (TRX), Polygon (MATIC), Shiba Inu (SHIB), Luna (LUNA), Ava (AVA), SafeMoon (SAFEMOON), Uniswap (UNI), and Axie Infinity (AXS).

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 than 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 – albeit only suggestive – response rate to celebrity financial advice. When focusing only on investors who saw her post we find that compliers were more likely to be male, young, and live in urban areas, but that there were no differences by race or education. The evidence from the survey suggests that i) 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 potentially act upon them.

Next, we dig deeper into the question of who invests in cryptocurrencies and follows the investment advice of real-life celebrities using transaction-level data from Albert, an account aggregator fintech firm. 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), which we term "crypto investments." Using a stacked event-study design we find that on days with celebrity tweets the probability of investing in crypto increases by 16% relative to baseline. This increase in investment probability is short-lived, as it occurs on the day of the tweet and returns to baseline the following day. 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 then explore the characteristics of Albert investors that act on celebrity tweets. Men, wealthier users and older users are more likely to react to celebrity endorsement. We further test whether certain types of celebrity are more effective in moving their followers to action, but find a largely homogeneous effect across influencer classes (e.g., sports stars vs. actors vs. musicians). 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 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 above shows that individuals respond to celebrity influencers' 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 examine the returns and trading volume in the week leading up to and the week following the tweets. In an event-study design we find that a celebrity tweet is associated with a 3.6% increase in returns and a 16% increase in trading volume on the day of the tweet. While the return effect is limited only to the day of the tweet, the trading volume remains elevated for several days following the tweet. When we separate results by coins we find that the return effect is absent from Bitcoin and Ether, whereas trading volume is elevated for all coins on the day of the tweet, and lasts longer for DOGE and the rest of the coins. This heterogeneity by coins is consistent with celebrity influencers having larger aggregate effects on relatively smaller cryptocurrencies, for which retail investors might represent a bigger share of total demand. Also in line with our mechanism, when we split our tweets by Twitter attention (as measured by likes, replies, quotes and retweets) we see much stronger effects in the high attention subsample than we do in the low attention one.

To increase our confidence in the causal nature of our results we next perform a difference in differences (DID) analysis where we use coins that are not affected by a celebrity tweet in the event window as controls. Specifically, we add to the event study dataset all the non-stablecoin cryptocurrencies in the top ten currencies on CoinMarketCap.com. In this more controlled setting, we find that celebrity tweets are associated with a 3% increase in returns and a 10% increase in trading volume, driven by all the coins except for Bitcoin and Ether. Unlike the more persistent results of the event study, the aggregate volume effect lasts for 2 days after the tweet before it disappears.

In the final part of the paper we examine how individual investors would have performed buying the coins after they see the tweet. First, we find that trading volume increases by roughly 20% in the hour surrounding celebrity tweets, but is already elevated in the days leading up to the tweets and stays high for at least two days. Individuals trading in the hours leading up to the tweets are either insiders or bought the coins by chance. Retail investors are likely to be buying the coins after the tweets. While we don't observe exactly when retail investors purchase the coins, we examine how investors would have performed had they bought the coins in the hours following the tweets. We find that investors who bought before the tweets and sold after would have had an average performance of 2.9% whereas investors who bought after and sold after the tweets would have only made 0.8%. We then compare these returns to how they would have done had they bought Bitcoin (or Ethereum if the coin in question is 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 -0.2%, 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)). 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. One of our core contributions is to examine the demographics of investors who follow the advice of celebrity influencers.

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 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. (2022)). 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, as ICOs are the earliest stage in the cryptocurrency lifecycle, while we examine late-stage 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 company ran in September 2021 a survey of more than 2,000 adults in the US to understand household view of celebrities and their impact on financial decisions, with a focus on the June 14, 2021 post on Instagram by Kim Kardashian and the cryptocurrency industry. 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 demographics variables (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 assemble 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 exchange. We supplement 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 omit 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 3 lists the 75 celebrities, the number of crypto tweets that each posts in our sample, the number of Twitter followers, 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 then collected every available tweet posted by the celebrities on our list, and run all tweets through a regular expressions filter that identifies and keeps tweets with the terms mentioned in Table A1.[5] 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 keep tweets about the 14 cryptocurrencies that are not stablecoins and that appear in least 25 separate tweets in our dataset. These are: Bitcoin (BTC), Ether (ETH), Doge (DOGE), Ripple (XRP), Cardano (ADA), Solana (SOL), Tron (TRX), Polygon (MATIC), Shiba Inu (SHIB), Luna (LUNA), Ava (AVA), SafeMoon (SAFEMOON), Uniswap (UNI), and Axie Infinity (AXS).

Table 11 shows the number of tweets per coin-day. That is how many events – defined as separate days in which there is at least one tweet about a coin – we have per coin. Bitcoin makes up 44 percent of the tweet days, with Ether and Doge each making up another 15 percent, and most coins have around two tweets per event.

We source our data on cryptocurrency closing prices and daily volumes from CoinMarketCap.com. To avoid stale data affecting our results we replace volume with a zero if it is identical to the previous day's volume, and drop prices for days with zero or missing volume.

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.

We use 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

[5]Words 'yummy', '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 require that they are preceded by either a "#" or a "$".

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*.[6] 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 5 presents the summary statistics of main user-level variables.[7] Figure 1 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 33. Income is more similar to the overall population, although also 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 5 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 to have a higher income (for a comprehensive analysis of the demographics of crypto investors, see Pursiainen and Toczynski 2022). Figure 1 shows that they are similar to the full sample in terms of age, but have somewhat higher incomes. Our investors deposited a cumulative total of over $3,000 on average into their cryptocurrency

[6]Table A4 in the appendix includes the list of keywords we used to identify cryptocurrency transactions. Most identified transactions come with the title *Coinbase*.

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

accounts over the course of our over two and a half year sample, although 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 StockTwits

StockTwits is a social media messaging app that was launched in 2008, and since then the platform has grown rapidly – in 2020, users generated over 6.5 million tweets per month. StockTwits has been used in prior literature to study how activity on financial social media affects financial markets (e.g., Cookson and Niessner (2020), Cookson et al. (2023)), as well as whether there are certain authors that have predictive power (Kakhbod et al. (2023)). Kakhbod et al. (2023) use the sample from July 2013-January 2017 and they focus only on stocks. We extend the sample through 2021, and examine both stocks and cryptocurrencies.. We examine the time period January 2013 - December 2021 for stocks and January 2018 - December 2021 for cryptocurrencies.

3. Survey Evidence From the "Largest Financial Advice In History"

In this section we provide survey evidence on the characteristics of investors who follow celebrity influencers' financial advice. We first focus on the followers of 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"*. 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 following story:

"ARE YOU GUYS INTO CRYPTO????

THIS IS NOT FINANCIAL ADVICE BUT SHARING WHAT MY FRIENDS JUST TOLD ME ABOUT THE ETHEREUM MAX TOKEN!

A FEW MINUTES AGO ETHEREUM MAX BURNED 400 TRILLION TOKENS-LITERALLY 50% OF THEIR ADMIN WALLET GIVING BACK TO THE ENTIRE E-MAX COMMUNITY.

#EMAX #DISRUPTHISTORY #ETHEREUMMAX #WTFEMAX #GIOPEMAX #ETHEREUMMAX #AD".[8]

Using data from a nationally representative survey with over 2,000 respondents conducted by Morning Consult we explore the determinants of overall holdings of cryptocurrencies and investment in Ethereum Max following the Kim Kardashian post.

We begin by looking at the role of investor demographics. Column 1 of Table 1 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 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, column 2 of Table 1 investigates the demographics associated with a higher likelihood of having seen, read, or heard about the Kim Kardashian Instagram post on Ethereum Max. Young males 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 know 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. 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, column 3 of Table 1 shows the results of 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. About 20% of respondents who saw the post say they ended up investing in Ethereum Max, which suggests that celebrity influencers can

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

potentially have a large impact on household asset allocation.

The followers this celebrity influencer's financial advice share several characteristics with cryptocurrency holders. They are more likely to be male (even if the effect is only marginally significant), young, and live in urban areas. However, followers of financial advice from celebrity influencers also differ from 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.

We then explore the role of opinions about celebrity influencers in Table 2. All columns control for demographic characteristics, since we want to study the marginal effect of opinions about celebrity influencers on the receptiveness of their advice. In column 1 we look at crypto holdings. As a placebo, we show that positive or negative opinions about Kim Kardashian (and Elon Musk) are not associated with differential overall holdings of cryptocurrencies. Column 2 shows that respondents with positive (negative) opinions about Kim Kardashian are more (less) likely to have seen the post. These results are consistent with fans being more attentive than nonsupporters to influencers' posts.

Finally and most importantly for our mechanism, 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. This result suggests that influencers' popularity might spill over beyond their area of expertise and into retail investment choices. Table A2 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. Individual-level evidence from an Aggregator App

In this section, we analyze transaction-level data gathered by a fintech firm to explore the extent to which retail cryptocurrency investors follow celebrity influencers' financial advice, and the characteristics of those who do.

To operationalize our analysis we first aggregate users' flows into and out of cryptocurrency accounts at the user-day level (it). Since investment transactions from weekends and holidays only get booked on the next business date, we restrict our sample to business days and any tweets that happen on weekends or holidays are assigned to the nearest subsequent working day. We treat each tweet as an event, keeping a window spanning six days before and after each tweet for each individual, and we stack each 13-day-long event for each individual into a dataset at the event×day×individual level.[9] To analyze the impact of tweets on investment flows, we estimate the following event-study specification:

$$\begin{aligned} Outcome_{eti} = &\sum_{h=-6}^{6} \alpha_h \times tweet_{e,t_0+h} + \gamma_e + \lambda_{dow(t)} + \xi_i \\ &+ \rho_t + \phi_{pre}\mathbb{1}_{et}^{Pre\ tweet} + \phi_{post}\mathbb{1}_{et}^{Post\ tweet} + \epsilon_{eti} \end{aligned} \tag{1}$$

where $Outcome_{eti}$ is an indicator for either an investment or a withdrawal transaction. $tweet_{t_0+h}$ is an indicator equal to 1 at time $t_0 + h$, where t_0 is the day of the tweet. In this specification the coefficient α_h estimates the treatment effect for day h relative to t_0. We include day of the week fixed effects ($\lambda_{dow(t)}$) to absorb any variation that comes from different levels of attention across days of the week or clustering of weekend transactions on Mondays. Because our data stacks 13 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 observations before and after each tweet might also fall on days when other tweets in our database occurred these days may reflect changes in trading due to another event. To account for this, we add indicator variables $\phi\mathbb{1}_{et}^{Pre\ tweet}$ and $\phi\mathbb{1}_{et}^{Post\ tweet}$ which equal 1 if there is another tweet on day t in the pre and post periods respectively.[10]

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

[10] Comment: this design might leave some bias working against our result since it compares *"contaminated"* control observations to *"clean"* control observations and true events, and due to the latter it might

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. We use a conservative approach double-cluster the standard errors at the user and day level.

4.1 Dynamic effects

Figure 3 presents the dynamic treatment effects obtained by estimating equation 1 with an indicator for a crypto investment as the dependent variable. The coefficients are close to zero and statistically insignificant in the days leading 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 nearly 16% relative to the baseline. The flow effect is short-lived and dies out on the following day.

In Figure 4, we further re-estimate the model separately for Bitcoin, Ether, DogeCoin, and the other coins in our sample. We find the same response of investment on the day of the tweet for each coin, although the effect is the strongest for DOGE and more muted (and not statistically significant) for the "other coins" category. These estimates show that individual investors respond to celebrity financial advice delivered via social media by depositing money into their crypto investing accounts immediately following a tweet.

4.2 Heterogeneity analysis

Next, we explore the characteristics of the individuals that respond 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 between -3 and 3 days around the event and use a random 50% of the investors. Further, as the estimation results of equation 1 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 1 as follows:

$$\begin{aligned} Outcome_{eti} = \alpha_0 tweet_{et_0} + \alpha_z (tweet_{et_0} \times Z_i) + \gamma_e + \lambda_{dow(t)} + \xi_i \\ + \rho_t + \phi_{pre} \mathbb{1}_{et}^{Pre\ tweet} + \phi_{post} \mathbb{1}_{et}^{Post\ tweet} + \epsilon_{eti} \end{aligned} \quad (2)$$

underestimate the size of the correction.

Z_i are investor-level characteristics and the base levels of Z_i are absorbed by user fixed effects ξ_i.

Table 6 presents our baseline results. Column 1 shows that a celebrity tweet corresponds, on average, to an increase in the probability that a retail investor makes a cryptocurrency investment of around 10% relative to the base level on the day of the tweet. 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), but does not appear to be related to 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. Appendix Table A3 repeats this exercise for withdrawals from cryptocurrency accounts; we find men are slightly more likely to withdraw funds in response to celebrity tweets, but unlike for investments, other characteristics are largely insignificant, likely reflecting that withdrawals are relatively rare overall.

We find substantial consistency of our results. Table 7 tests for heterogeneous effects by which cryptocurrency a tweet focuses on. Overall, there is no detectable difference in effect across coins: while the response to tweets about DogeCoin is largest (consistent with Figure 4), the interaction term is not statistically significant. In the same vein, Table 8 explores whether different categories of influencer have stronger effects. To this end, we include interactions of *Event* 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. None of the estimated interaction terms are economically or statistically significant, indicating that the effect we estimate is relatively homogeneous across influencer categories. Importantly, this also shows that our findings are not driven by responses to tweets by particular high-profile individuals such as Elon Musk.

Next, we test whether race and political affiliation influence heterogeneity in response to celebrity tweets. To this end, we include interactions with matched county-level demographic variables: shares of racial groups in the population and shares of registered voters according to political affiliation. The results are presented in Table 9. We find that investors living in counties with a higher Black population share are less likely to respond to influencer tweets about cryptocurrencies, while people from areas with a high Asian population share are more likely to respond. By contrast, there are no economically or statistically significant differences by political affiliation.

Finally, we analyze whether celebrity tweets are correlated with first-time investments. If influencers encourage retail investors to enter the cryptocurrency market, their long-term impact on cryptocurrency flows is likely underestimated by our baseline models. To this end, we split cryptocurrency deposits into extensive and intensive margins. In the case of the former, we model how a tweet event affects the probability of making the first investment. Since we do not observe users' activity before mid-2020, we only consider a deposit as generating an entry into crypto investing (i.e., the "extensive margin") if we do not observe a user making any cryptocurrency transactions in the first 6 months of the 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% (column 4). The magnitude of the effect is slightly smaller in the case of extensive margin; here, on the day of a tweet the probability of an investment increases by over 8% relative to the baseline (column 6).

5. Aggregate Evidence

In this section we explore the return and volume impacts of celebrity tweets that mention specific cryptocurrencies. We begin with event studies to visualize the effect on the focal currency, and then use a difference in differences specification to enable a causal interpretation of the effects we estimate.

5.1 Event Study

We prepare the event study analysis by treating each tweet as an event, keeping a window spanning six days before and after each tweet and stacking the data from each of the 948 events in our sample.[11] We estimate the following specification:

$$\begin{aligned} Outcome_{et} = \sum_{h=-6}^{6} \alpha_h tweet_{e,t_0+h} + \gamma_e + \lambda_{dow(t)} \\ + \phi_{pre} \mathbb{1}_{et}^{Pre\ tweet} + \phi_{post} \mathbb{1}_{et}^{Post\ tweet} + \theta X_{et} + \epsilon_{et} \end{aligned} \tag{3}$$

The $Outcome_{et}$ for event e in period t is return or trading volume. α_0 is the estimated effect of the tweet on the day of the tweet (day t_0), while the remaining α_h coefficients provide estimates for each of the days preceding or following the tweet. Because our data stacks 13 day event windows we include a vector of event fixed effects (γ_e) and cluster standard errors by event. We include day of the week fixed effects ($\lambda_{dow(t)}$) to absorb any variation that comes from different levels of attention across days of the week. We also include a fixed effect for days in our event window on which one of our celebrities tweets about the focal coin in the six days before the tweet ($\mathbb{1}_{et}^{Pre\ tweet}$) and similarly for the six days after $\mathbb{1}_{et}^{Post\ tweet}$).[12] Finally, to capture any pre-event serial correlation in the outcomes, we include a vector of controls (X_{et}), all measured for the period $t-30$ to $t-7$; these are (i) the cumulative return for the focal cryptocurrency, (ii) the standard deviation of its returns and (iii) its mean log volume.

Figure 5 plots the estimates obtained from pooling all events. Panel (a) shows that returns appear to spike by 3.6 percentage points on the tweet day, with largely flat pre-and post tweet returns, and so no price reversal (see Table 12). Panel (b) shows a much stronger effect for volume, which jumps to 16 log points above baseline on day 0. The estimate for day -1 shows some anticipation in trading volume, which would be consistent with insiders knowing of an upcoming tweet and positioning accordingly. While the spike in returns disappears after day 0, volume remains above baseline for the next 6 days.

Celebrity tweets attract public attention, and some fraction of this attention is converted into individuals deciding to trade as a result. Figure 6 splits the sample into above and below median attention on the day of the focal tweet, defining attention as the sum of likes, retweets, quote tweets and replies. Consistent with the tweets we identify being the channel

[11] We collapse the data to the cryptocurrency-day level so that coins mentioned in multiple tweets mentioning in a single day are treated equivalently to a coin that receives a single tweet in a day.

[12] Coefficients are similar if instead we exclude all 643 events in which there are any tweets in the six days before the focal tweet, with day 0 coefficients (s.e.) for returns and log volume of 0.048 (0.032) and 0.133 (0.035) respectively.

driving the results, we find that high attention tweets have substantially higher tweet-day returns and volume than the pooled results. Despite this, there is still a small day zero spike in returns, albeit statistically insignificant, for the low attention subsample and a larger and more persistent spike in log volume.

Table 12 presents the pooled event study estimates in the first two columns and subsample estimates by cryptocurrency in the remaining ones. Bitcoin returns show no responsiveness to celebrity tweets on day zero, consistent with this being the most liquid coin, but trading volume rises by 6 log points and stays higher for the two subsequent days (columns 3 and 4). Estimates for Ether are similar: no return effect on the tweet day, coupled with a spike in volume, with some evidence of elevated trading on subsequent days. By contrast, Doge shows a 10 percentage point spike in returns on day zero, with no evidence of increased returns or of reversal on subsequent days, and only weak, noisy evidence of anticipation effects on returns on days -2 and -1. Volume also rises markedly on day zero, by over 50 log points, declining but remaining elevated out to day +6. While not statistically significant, the estimated volume of 13 log points above baseline on day -1 suggests possible anticipatory trading. Finally, in columns 9 and 10 we pool the events for the remaining coins and find similar patterns to those for Doge. Specifically, a spike in returns on day zero only, and a persistently higher trading volume that declines from the high of 20 log points on day zero.

5.2 Difference in Differences Analysis

We next turn to a difference in differences (DID) specification that uses a similar structure to the event study analysis, but adds control coins. Specifically, we add to the event study dataset all the non-stablecoin cryptocurrencies in the top ten currencies on CoinMarketCap.com, which are Bitcoin, Ether, Ripple (XRP), Cardano (ADA), Dogecoin, Solana (SOL), and Tron (TRX). We drop all control coins that themselves have a tweet in the event window so that our staggered DID specification on stacked events uses only non-treated units as controls, thus ensuring that we do not make "forbidden comparisons" (Borusyak et al., 2021). Because the latter reduces the number of control coins for some events, we drop events with only three or fewer control coins, leaving us with 674 separate events in the DID analysis. We estimate the following specification:

$$
\begin{aligned}
Outcome_{etc} = \delta Treated_{ec} + \sum_{h=-6}^{6} \alpha_h tweet_{e,t_0+h} + \sum_{h=-6}^{6} \beta_h (tweet_{e,t_0+h} \times Treated_{ec}) \\
+ \gamma_e + \lambda_{dow(t)} + \theta_c + \phi_{pre} \mathbb{1}_{et}^{Pre\ tweet} + \phi_{pre} \mathbb{1}_{et}^{Post\ tweet} + \theta X_{etc} + \epsilon_{etc}
\end{aligned}
\tag{4}
$$

As with equation 3, e indexes 13 day event windows, in period t for the treated cryptocurrency c. This specification differs from equation 3 by the addition of a $Treated_c$ indicator and the interactions of this variable with the event-time indicators ($tweet_{t_0+h}$). A second difference with equation 3 is that this specification also includes a coin fixed effect (θ_c), given that we have multiple coins per event. All other specification components are identical: event and day of the week fixed effects, plus fixed effects for cases when the treated coin has celebrity tweets in the 6 days before or the 6 days after the focal tweet ($\phi \mathbb{1}_{et}^{Pre\ tweet}$ and $\phi \mathbb{1}_{et}^{Post\ tweet}$) and a vector of pre-determined controls (X_{etc}).

Figure 7 panel (a) plots the estimates for the event-time indicators interacted with the Treated indicator, capturing the estimated DID effect on the treated coins. Overall, results are quite similar to those in the event study analysis. Pre-trends are largely flat, except for returns rising slightly on the day before the tweet. There is a clear spike on day zero in both returns and log trading volume, with no subsequent effect for returns, while log volume remains above baseline for two subsequent days. Panel (b) plots the equivalent coefficients for the control coins; these are flat throughout, suggesting that little is occurring with these coins in the event window.

Table 13 presents the estimated DID coefficients corresponding to the regressions in Figure 7 in columns 1 and 2. These match the plots: a 3 percentage point spike on day zero for returns (as well as a 1 percentage point increase on day -1), with no subsequent reversal. For log trading volume there is a much larger spike on day 0 (and flat pretrends before) of almost 10 log points, followed by above-baseline trading of around 5 log points for two subsequent days.

The remaining columns in the table disaggregate the pooled results in columns 1 and 2 by coin. While this greatly reduces the statistical power of our empirical exercise it allows us to examine heterogeneity in response across coins. Columns 3 and 4 focus on the subsample of events that have celebrities tweeting about Bitcoin; these show no evidence of an effect on returns. There is some increase in the point estimate for days 0, 1 and 2 for log volume, but this is small (only 1-2 log points), and not statistically significant. For Ether there is also no effect on returns – except for a relatively small positive return estimate for day -1 – but the estimates suggest increased trading volume for days -1 to 2, although they are mostly not statistically significant. Estimates for Doge returns show a spike of 5 percentage points on day 0, with weak evidence of a 1.7 percentage point higher return on day -1, and no reversal in the days following the tweet. Trading volume also spikes by 36 log points on day 0, but falls back to baseline quickly after. The final two columns pool the events for the remaining eleven coins, and show some evidence that returns rise above baseline on day -1 and on day 0, although the estimates are only significant at the 10 percent level, and the estimates for subsequent days are too noisy for statistical significance. Volume appears to begin its rise on day -2, consistent with potential trading in anticipation of a celebrity tweet, and consistent with the suggestive evidence of rising returns in column 9. However, the estimate is only statistically significant, given the limited statistical power of this subsample, for the volume spike of 18 log points on the day of the tweet. Volume stays above baseline for four days based on coefficients, but only the first two are statistically significant.

In summary, the DID evidence parallels the evidence provided by the event studies in that both show large spikes in returns and volume on the day of the tweet, with no reversal on returns and some days of persistently higher trading volume. Bitcoin shows no evidence of a return or a volume spike, while Ether displays a volume increase and Doge and the other coins show large effects for both returns and volume on the tweet day.

6. Advice Quality

In the last two sections we have demonstrated that individual investors trade based on real-life celebrities' crypto-related tweets. 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 obtain hourly-level data from FirstRate.com for six major coins: Cordano (ADA), Bitcoin (BTC), Ethereum (ETH), Dogecoin (DOGE), Tron (TRON), and Ripple

(XRP). We begin by examining the performance of trades in the days and hours around the tweets, and compare them to counterfactual trading opportunity.

6.1 Trading around the Tweets

First, we examine the trading volume around tweets at the hourly level. We look at 2 weeks before and after each tweet. Figure 8 presents the results. On the x-axis are hours relative to the tweet, and on the y-axis is the average log trading volume for a given hour. All the observations are scaled by the log trading volume at during the hour -336. The figure shows that the volume gets slightly elevated about a week before celebrity tweets (-168 hours), and then starts increasing sharply around 48 hours prior to tweets. The speed of the increase accelerates as the hours get closer to the tweets. The trading volume during the hour of the twee is 20% higher than the base level. The volume stays elevated for about 24-48 hours before returning back to the pre-tweet levels. This graphs provides evidence that there is trading in the days before and after the tweet. Next, we examine how investors would perform if they trade in the time around the tweets.

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 around the tweet, and selling intervals after the tweets. The first set of results are presented in Figure 9, 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 on an international brokerage cite eToro Kogan et al. (2023). We assume that 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 retail investors would not have advance notice of the impending tweet, and thus would have purchased the coin in the post-tweet period.

In Figure 9, Panel A, the deeper the red color, the smaller 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). 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. Retail investors are going to be disproportionately in the post-post group. The average return of the pre-post period is 2.9% and in the post-post period it's 0.8%. The difference is statistically significant at the 1% level. While the return is significantly higher if the purchase occurred before the tweet, it's still positive if the coin was bought after the tweet.[13]

When considering the return of 0.8% 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 proxy for several counterfactuals. First, we construct abnormal returns - returns relative to Bitcoin, which is often viewed as the market return in cryptocurrencies. Since we can't use Bitcoin returns to calculate abnormal returns for Bitcoin trades, for tweets about Bitcoin we use Ethereum as the market return - which is the second most-traded coin. We repeat the analysis similar to Panel A, except we use abnormal returns – returns minus the 'market' return. We present the results in Figure 9, Panel B. 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. Comparing the pre-post trades to post-post trades, the average abnormal return for the pre-post trades is 1.9% and the average abnormal return for the post-post trades is -0.2%. The results are statistically significant at the 1% level. This suggests that even before trading costs, retail investors lost money if they bought following a celebrity tweet.

[13]Given the high fees of roughly 1% for trading cryptos on exchanges like Coinbase (https://help.coinbase.com/en/commerce/getting-started/fees), the 0.8% return on the post-post trades will easily be wiped out by the trading fees.

7. Conclusion

As younger adults look to social media for news and financial advice, especially for cryptocurrencies, a new group of 'financial advisors' has emerged with an unprecedented reach – celebrity influencers. We combine survey responses and transaction-level data with real-life celebrities' Twitter crypto-related posts to study how celebrity endorsements shape households' financial decisions. We find that a celebrity tweet is associated with a 10% increased probability of investing in cryptocurrencies, with the effect being stronger for men, wealthier, and older users. We further find that aggregate trading volume increases by 10% on the day of the tweet and stays elevated for the following two days, while returns exhibit a 3% spike with no reversal in the following week. We conclude by comparing celebrity influencers to traditional social media Finfluencers find that their crypto-related posts are associated with higher contemporaneous and future returns.

As the number of lawsuits against celebrities mounts, it's important to understand 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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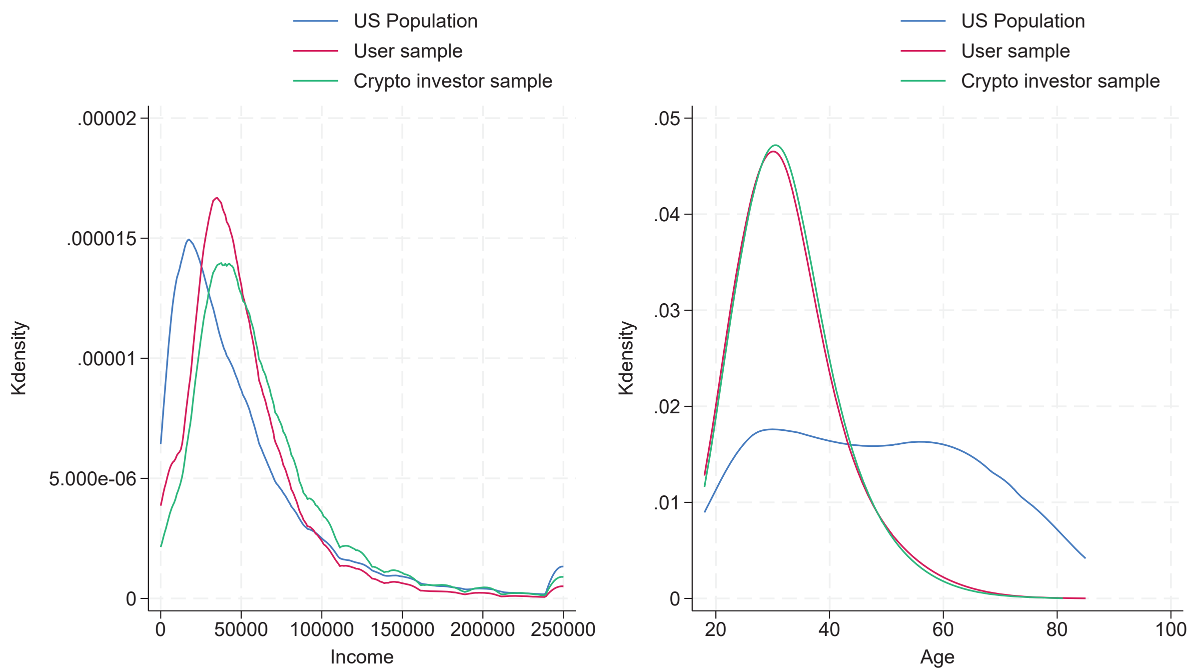
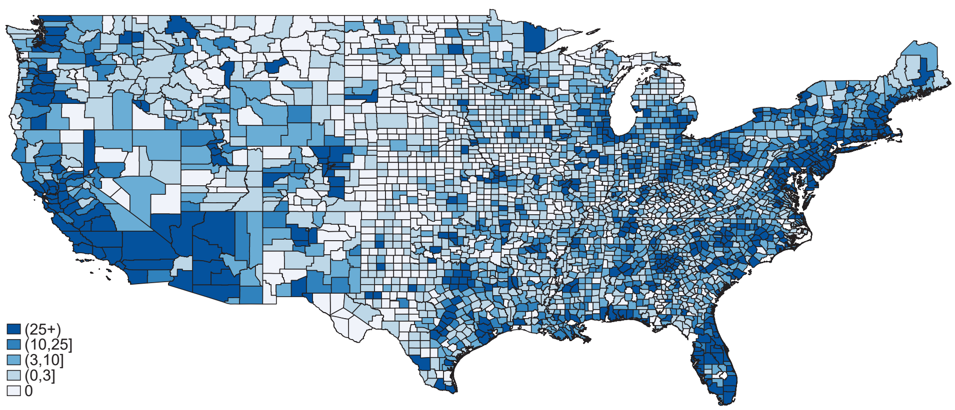
Figure 1: Comparing our individual data sample to the U.S. population



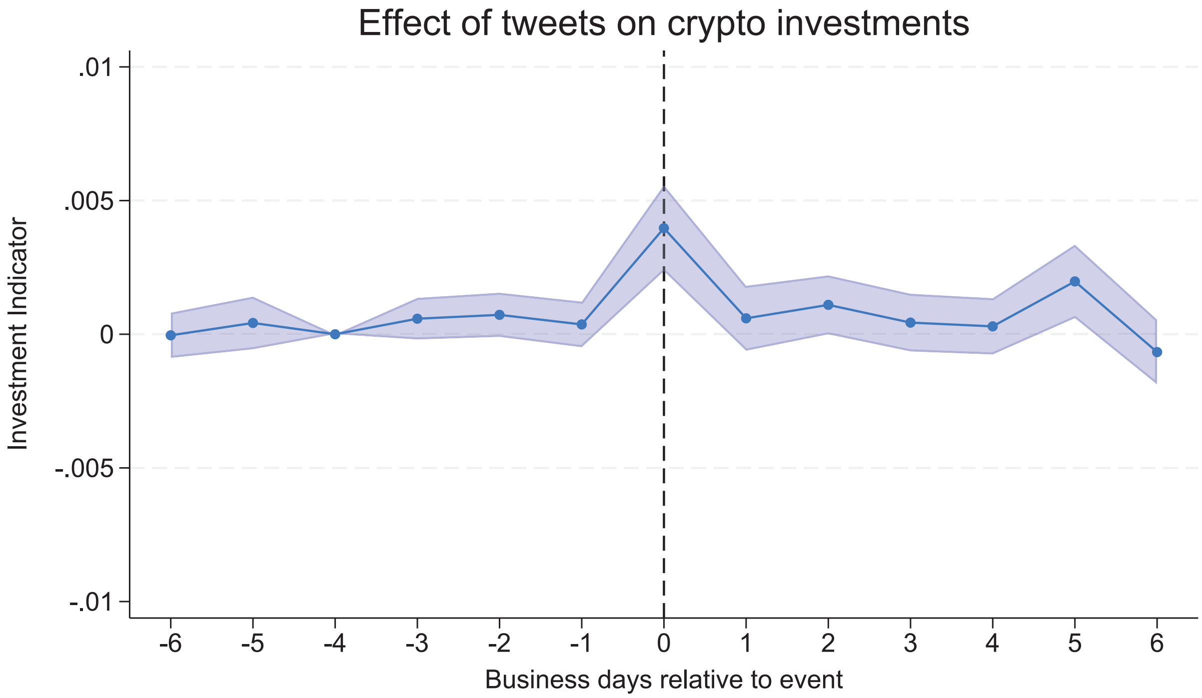
Note: U.S. data from the 2020 Current Population Survey.

Figure 2: Geographical distribution of users in our sample



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

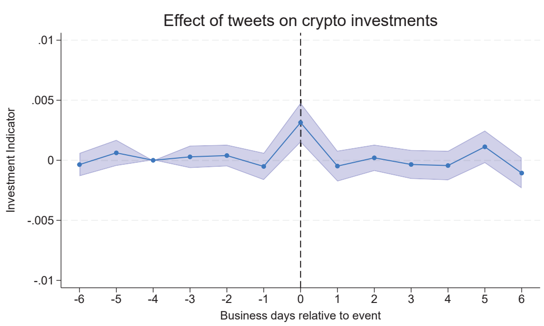
Figure 3: Dynamic investment response



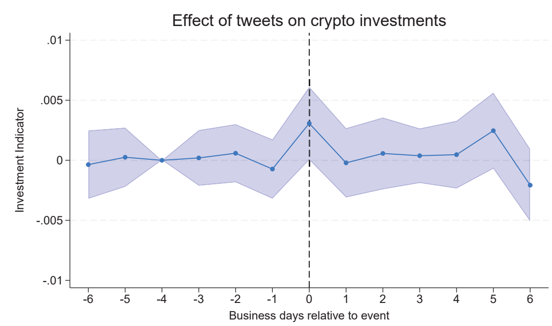
Note: This figure plots the estimated treatment effect coefficients from equation 1. The dependent variable is an investment indicator. Day -4 is the reference category. 95% confidence intervals double clustered at the user and day level.

Figure 4: Effects by coin

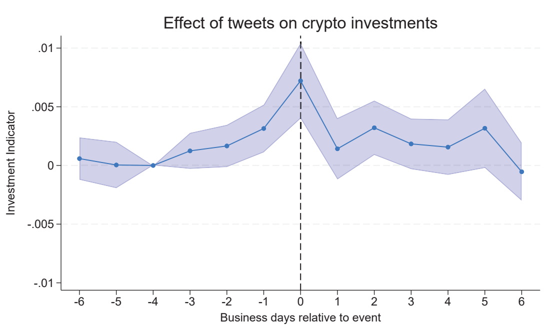
(a) BTC



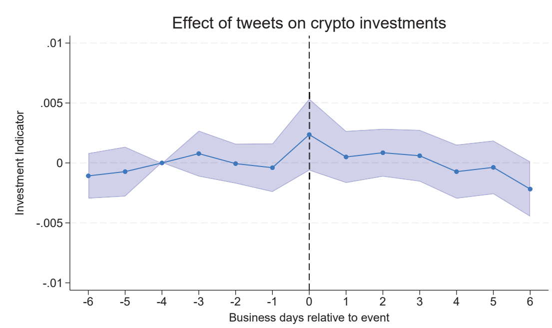
(b) ETH



(c) DOGE



(d) OTHERS



Note: This figure plots estimated treatment effect coefficients from equation 1. The dependent variable is an investment indicator. Day -4 is the reference category. 95% confidence intervals double clustered at the user and day level.

Figure 5: Event Study - Aggregate Effects

(a) Return **(b)** Volume

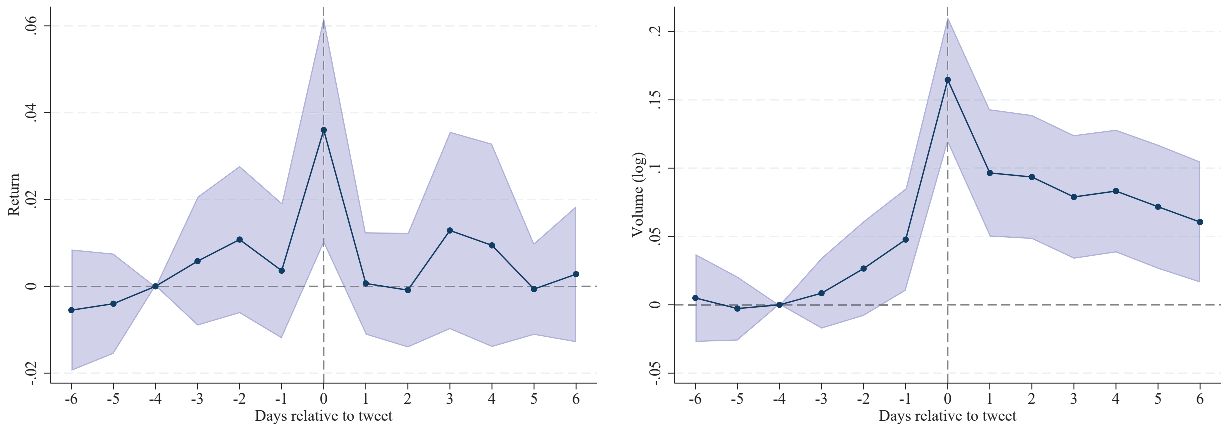


Figure 6: Event Study - Aggregate Effects by Attention

(a) High attention **(b)** Low attention

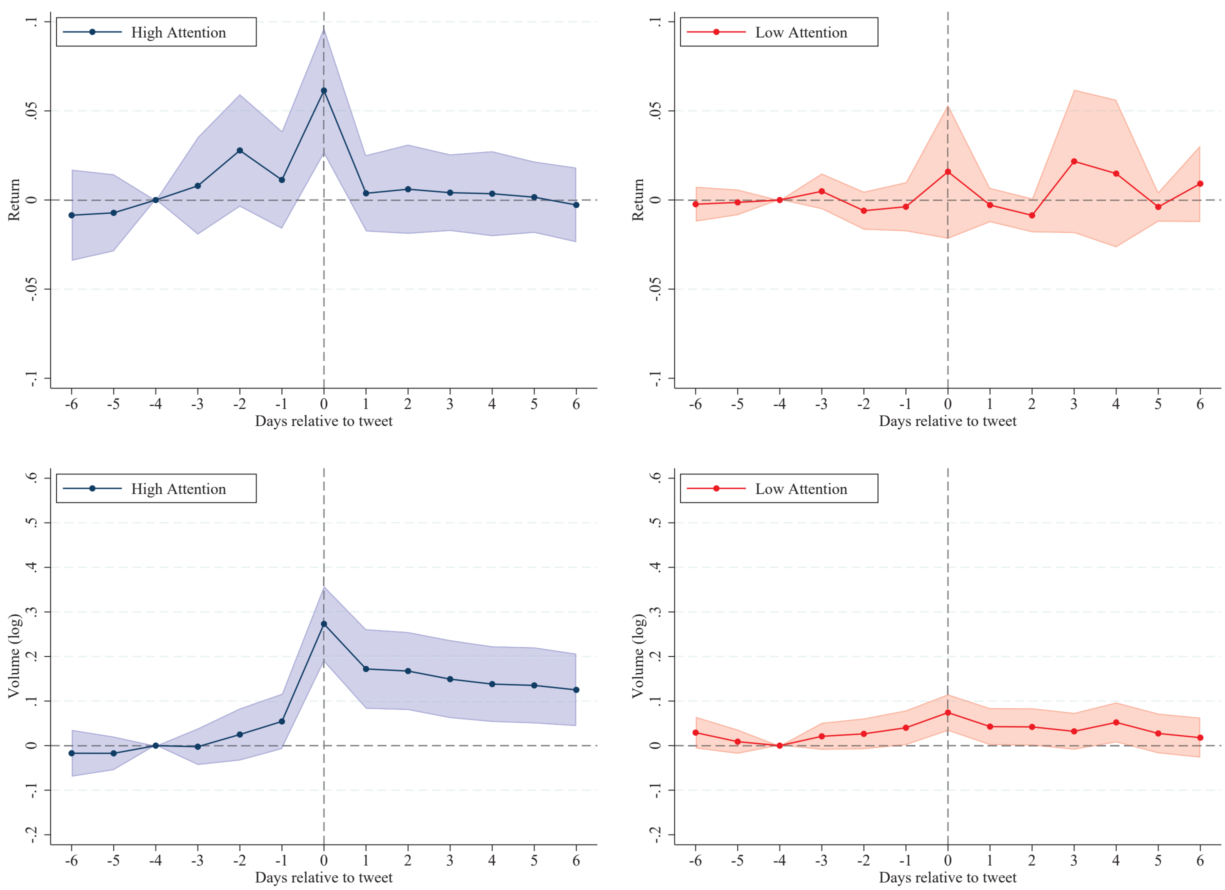


Figure 7: Difference in Difference estimates

(a) Treated **(b)** Control

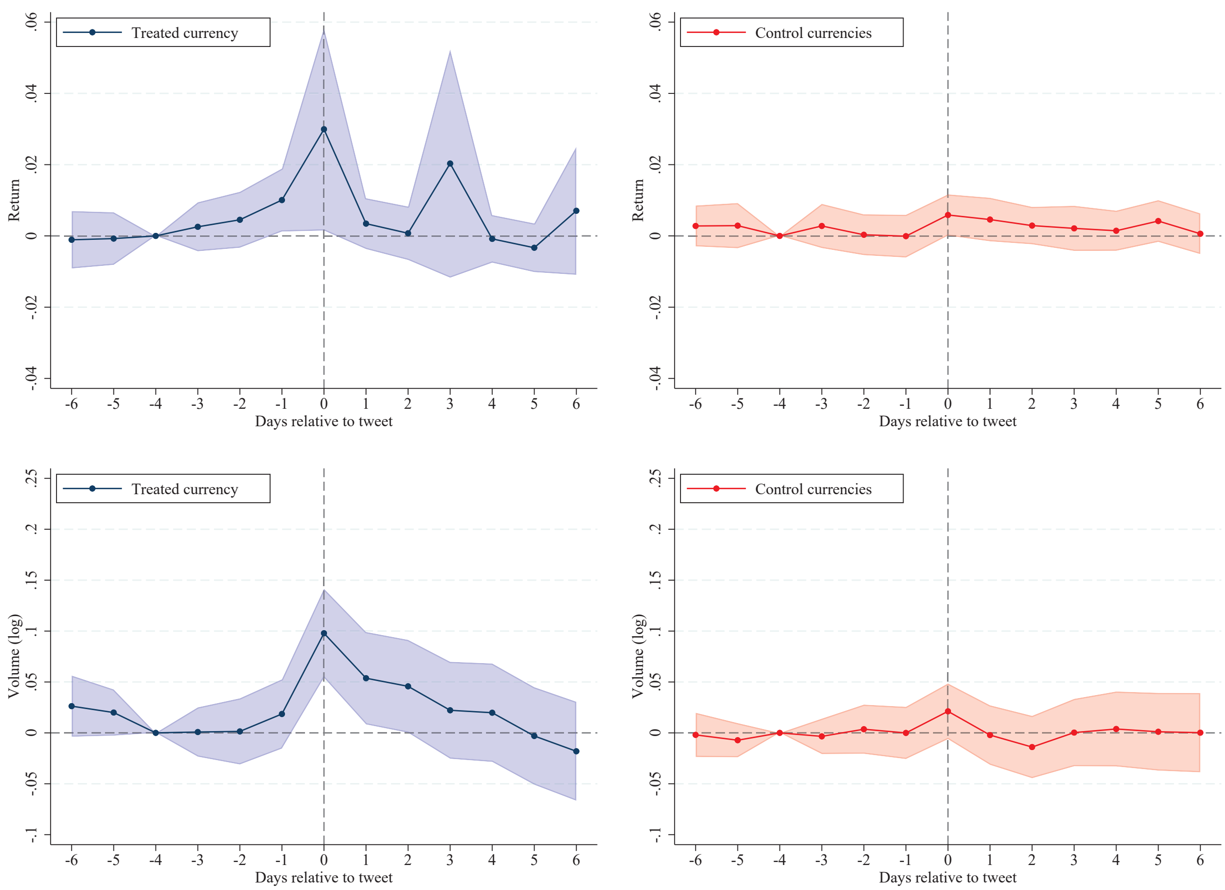
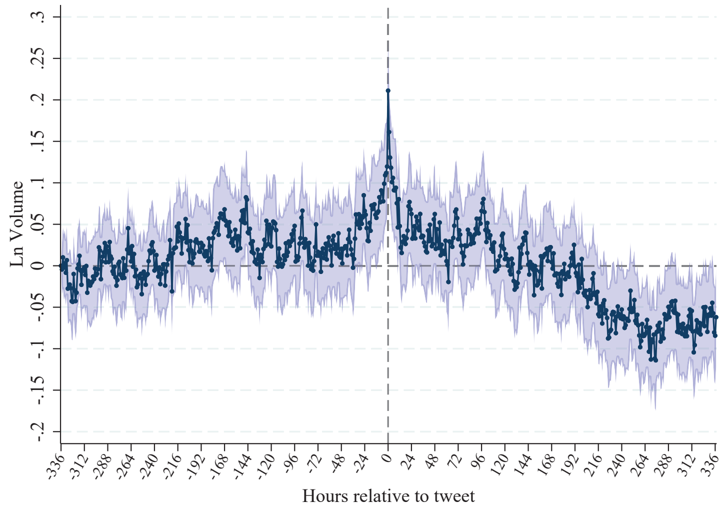


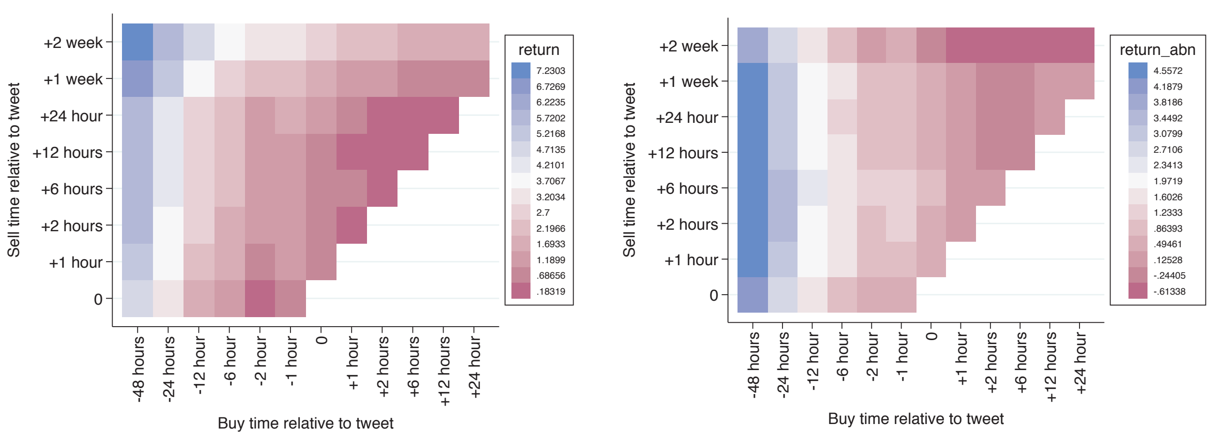
Figure 8: Trading volume around the Tweets



Note: This figure presents the hourly log trading volume for -/+366 hours (2 weeks) around celebrity tweets. The values are relative to log volume at hour -366.

Figure 9: Trading Returns

(a) Raw returns **(b)** 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 abnormal returns - returns on the coins minus the return on BTC. For trades in BTC we subtract the returns on ETH.

Table 1: **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
Outcome SD	0.37	0.39	0.40
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 2: 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
Outcome SD	0.37	0.39	0.40
R^2	0.40	0.21	0.26
Obs.	2,200	2,200	399

Note: Standard errors are clustered at the firm and month×year level and reported in parentheses. *** 1%, ** 5%, * 10% significance level.

Table 3: Celebrities

USER NAME	NAME	NUM. TWEETS	NUM FOLLOWERS	CELEBRITY TYPE
RussellOkung	Russel Okung (NFL)	323	261,334	Sports
KEEMSTAR	Daniel Keem	235	2,600,000	Internet
mcuban	Mark Cuban	176	8,850,122	Shark Tank
elonmusk	Elon Musk	152	136,797,868	Elon Musk
stoolpresidente	Dave Portnoy	148	2,905,156	Celebrity
KaiGreene	Kai Greene	114	318,813	Celebrity
diplo	diplo	109	2,409,900	Musician
JBALVIN	JBALVIN	96	10,768,889	Musician
souljaboy	Soulja Boy	89	5,489,716	Musician
genesimmons	Gene Simmons	67	1,038,518	Musician
steveaoki	steveaoki	56	8,054,849	Musician
kevinolearytv	Kevin Oleary	49	984,522	Shark Tank
MattBarkley	Matt Barkley (NFL)	38	114,958	Sports
justinbieber	Justin Bieber	36	112,300,000	Musician
giseleofficial	Gisele Bundchen	35	4,600,031	Celebrity
ParisHilton	Paris Hilton	32	16,813,885	Celebrity
mattjames919	Matt James	24	77,354	Celebrity
lilyachty	Lil Yachty	23	5,418,662	Musician
deadmau5	Deadmau5	23	3,295,006	Musician
nickcarter	Nick Carter	23	693,931	Musician
ANGELAWHITE	Angela White	22	2,686,157	Celebrity
MKBHD	Marques Brownlee	21	6,032,929	Internet
jakepaul	Jake Paul	17	4,599,379	Internet
iamlorengray	Loren Gray	16	1,580,336	Internet
lindsaylohan	Lindsay Lohan	16	8,119,617	Celebrity
dennisrodman	Dennis Rodman (NBA)	15	464,400	Sports
mindykaling	Mindy Kaling	14	11,352,111	Celebrity
aplusk	Ashton Kutcher	13	16,875,977	Celebrity
miakhalifa	Mia Khalifa	13	5,443,443	Celebrity
ReeseW	Reese Witherspoon	12	2,974,758	Celebrity
SnoopDogg	Snoop Dogg	11	20,932,537	Musician
Madonna	Madonna	10	2,848,486	Musician
MeekMill	MeekMill	9	11,465,404	Musician
KingJames	LeBron James (NBA)	8	52,787,849	Sports
paulpierce34	Paul Pierce (NBA)	8	4,022,288	Sports
OfficialMelB	Mel B	7	965,500	Celebrity
MrBeast	Mr Beast	7	19,878,971	Internet
andre	Andre Iguodala (NBA)	6	1,358,004	Sports
StephenCurry30	Steven Curry (NBA)	6	17,386,048	Sports
KatGraham	Kat Graham	6	1,913,041	Musician
thegame	The Game	5	1,117,160	Musician
SHAQ	Shaquille Oneil (NBA)	5	15,949,635	Sports
MikeTyson	Mike Tyson (Boxer)	5	5,909,893	Sports
LilNasX	Lil Nas	4	8,056,152	Musician

Celebrity table (cont.)

USER NAME	NAME	NUM. TWEETS	NUM FOLLOWERS	CELEBRITY TYPE
Akon	Akon	4	6,104,181	Musician
saquon	Saquon Barkley (NFL)	4	507,123	Sports
FINALLEVEL	ICE T	4	1,944,173	Musician
LuisSuarez9	Luis Suarez (soccer)	3	17,673,100	Sports
serenawilliams	Serena Williams (tennis)	3	10,500,000	Sports
AB84	Antonio Brown (NFL)	3	1,637,146	Sports
Showtyme_33	Aaron Jones (NFL)	3	214,425	Sports
marcdamelio	Marc Damelio	3	662,785	Internet
FrencHMonTanA	French Montana	2	3,000,000	Musician
GuyFieri	Guy Fieri	2	3,529,380	Celebrity
JimmyButler	JimmyButler	2	963,982	Sports
tanamongeau	Tana Mongeau	2	2,400,000	Celebrity
obj	Odell Beckham Jr (NFL)	2	4,411,279	Sports
Maisie_Williams	Maisie Williams	2	2,479,874	Celebrity
KDTrey5	Kevin Durant (NBA)	2	20,800,000	Sports
KlayThompson	Klay Thompson (NBA)	2	1,847,493	Sports
pitbull	Pitbull	2	24,600,000	Musician
Pharrell	Pharrell Williams	2	10,455,064	Musician
GwynethPaltrow	Gwyneth Paltrow	2	2,705,301	Celebrity
KevinHart4real	Kevin Hart	2	37,379,187	Celebrity
jimmyfallon	Jimmy Fallon	1	50,500,000	Celebrity
GhostfaceKillah	GhostfaceKillah	1	868,000	Musician
TomBrady	Tom Brady (NFL)	1	3,073,808	Sports
JHarden13	James Harden (NBA)	1	7,765,688	Sports
ThisIsUD	Udonis Haslem (NBA)	1	395,430	Sports
CadeCunningham_	Cade Cunningham (NBA)	1	103,593	Sports
sc	Jay-Z	1	3,048,714	Musician
AaronRodgers12	Aaron Rodgers (NFL)	1	4,597,336	Sports
FloydMayweather	Floyd Mayweather (boxer)	1	7,754,818	Sports
iamjamiefoxx	Jamie Foxx	1	4,663,591	Celebrity
kevinjonas	Kevin Jonas	1	5,000,000	Musician

Table 4: 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 5: 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 6: Effect of Tweets on Cryptocurrency Deposits

	(1)	(2)	(3)	(4)	(5)	(6)
Event	0.0024***	0.0010*	0.0009*	0.0001	0.0016***	-0.0027***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0009)
Event × Male		0.0022***				0.0023***
		(0.0005)				(0.0005)
Event × Missing		0.0016***				0.0024***
		(0.0006)				(0.0007)
Event × Income>40k			0.0017***			0.0011**
			(0.0005)			(0.0005)
Event × Income>80k			0.0032***			0.0019***
			(0.0007)			(0.0007)
Event × Age>25				0.0020***		0.0016***
				(0.0005)		(0.0005)
Event × Age>35				0.0034***		0.0027***
				(0.0007)		(0.0007)
Event × CS: N/A					0.0002	0.0000
					(0.0006)	(0.0006)
Event × CS: Average					0.0008	0.0007
					(0.0007)	(0.0007)
Event × CS: Good					0.0012	0.0011
					(0.0007)	(0.0008)
Event FE	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y	Y
Tweet in Pre/Post FEs	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y
N. observations	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231
N. clusters indiv.	7,952	7,952	7,952	7,952	7,952	7,952
N. clusters date	612	612	612	612	612	612
R^2	0.134	0.134	0.134	0.134	0.134	0.134
Outcome mean	0.0256	0.0256	0.0256	0.0256	0.0256	0.0256
Outcome SD	0.1580	0.1580	0.1580	0.1580	0.1580	0.1580

The table presents the estimates of the linear probability model outlined in equation 2 for interactions with the event at relative time zero. The dependent variable is $Deposit_{i,t}$ which equals 1 if a user i made a cryptocurrency deposit at date t. The sample is at the *Event*, *Individual*, and *Date* level and spans from 3 days before the event to 3 days after. *Event* is an indicator variable marking the days when a celebrity tweet occurred. *CS* stands for credit score. *Missing* is an indicator for missing sex information. The sample is a random 50% of all data. Standard errors are clustered at the individual and event level and reported in parentheses. *** 1%, ** 5%, * 10% significance level.

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

	(1)	(2)	(3)	(4)	(5)
Event	0.0027***	0.0024***	0.0021***	0.0026***	0.0022***
	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
Event × BITCOIN	-0.0006				
	(0.0008)				
Event × ETHEREUM		0.0001			0.0003
		(0.0010)			(0.0011)
Event × DOGE			0.0020*		0.0019*
			(0.0010)		(0.0011)
Event × OTHERS				-0.0010	-0.0005
				(0.0010)	(0.0011)
Event FE	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y
Tweet in Pre/Post FEs	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y
N. observations	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231
N. clusters indiv.	7,952	7,952	7,952	7,952	7,952
N. clusters date	612	612	612	612	612
R^2	0.134	0.134	0.134	0.134	0.134
Outcome mean	0.0256	0.0256	0.0256	0.0256	0.0256
Outcome SD	0.1580	0.1580	0.1580	0.1580	0.1580

The table presents the estimates of the linear probability model outlined in equation 2 after adding interactions with dummies indicating tweets about specific cryptocurrencies (BITCOIN, ETHEREUM, DOGE, and OTHERS). The dependent variable is $Deposit_{i,t}$ which takes value 1 if a user i made a cryptocurrency deposit at date t. The sample is a grid identified by *Event*, *Id*, and *Date* and spans from 3 days before the event to 3 days after. *Event* is a dummy variable marking the days when a celebrity tweet occurred. DOW stands for day-of-the-week fixed effects and CS stands for credit score. The sample is a random 50% of all data. Standard errors are clustered at the individual and date level and reported in parentheses. *** 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	0.0024***	0.0024***	0.0021***	0.0024***	0.0024***	0.0026***	0.0025***	0.0018**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0008)
Event × CELEBRITY		-0.0001						
		(0.0008)						
Event × MUSIC			0.0017*					0.0020*
			(0.0009)					(0.0011)
Event × SPORTS				0.0003				0.0009
				(0.0010)				(0.0012)
Event × INTERNET					0.0001			0.0007
					(0.0012)			(0.0014)
Event × MONEY						-0.0014		-0.0006
						(0.0011)		(0.0013)
Event × ELON MUSK							-0.0004	0.0003
							(0.0013)	(0.0015)
Event FE	Y	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y	Y	Y	Y
Tweet in Pre/Post FEs	Y	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y	Y
N. observations	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231
N. clusters indiv.	7,952	7,952	7,952	7,952	7,952	7,952	7,952	7,952
N. clusters date	612	612	612	612	612	612	612	612
R^2	0.134	0.134	0.134	0.134	0.134	0.134	0.134	0.134
Outcome mean	0.0256	0.0256	0.0256	0.0256	0.0256	0.0256	0.0256	0.0256
Outcome SD	0.1580	0.1580	0.1580	0.1580	0.1580	0.1580	0.1580	0.1580

The table presents the estimates of the linear probability model outlined in equation 2 after adding interactions with dummies indicating types of celebrities. The dependent variable is $Deposit_{i,t}$ which takes value 1 if a user i made a cryptocurrency deposit at date t. The sample is a grid identified by *Event*, *Id*, and *Date* and spans from 3 days before the event to 3 days after. *Event* is a dummy variable marking the days when a celebrity tweet occurred. *DOW* stands for day-of-the-week fixed effects and *CS* stands for credit score. The sample is a random 50% of all data. Standard errors are clustered at the individual and date level and reported in parentheses. *** 1%, ** 5%, * 10% significance level.

Table 9: Heterogeneity by Race and Political Affiliation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Event	0.0024***	0.0029***	0.0018***	0.0020***	0.0026***	0.0023***	0.0022***
	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0007)	(0.0006)	(0.0007)
Event $\times Latino$	0.0000						
	(0.0010)						
Event $\times Black$		-0.0035***					
		(0.0010)					
Event $\times White$			0.0010				
			(0.0008)				
Event $\times Asian$				0.0066**			
				(0.0028)			
Event $\times Democratic$					-0.0005		
					(0.0011)		
Event $\times Republican$						0.0003	
						(0.0013)	
Event $\times Independent$							0.0006
							(0.0016)
Event FE	Y	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y	Y	Y
Tweet in Pre/Post FEs	Y	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y	Y
N. observations	41,142,326	41,142,326	41,142,326	41,142,326	41,365,792	41,365,792	41,365,792
N. clusters indiv.	7,895	7,895	7,895	7,895	7,895	7,895	7,895
N. clusters date	612	612	612	612	612	612	612
R^2	0.135	0.135	0.135	0.135	0.135	0.135	0.135
Outcome mean	0.0256	0.0256	0.0256	0.0256	0.0256	0.0256	0.0256
Outcome SD	0.1579	0.1579	0.1579	0.1579	0.1580	0.1580	0.1580

The table presents the estimates of the linear probability model outlined in equation 2 after adding interactions with location-level variables indicating either the county-level population shares of Latino, Black, White, and Asian populations respectively or the share of voters by political registration as of October 2020, using comprehensive voter roll data from L2. The dependent variable is $Deposit_{i,t}$ which takes value 1 if a user i made a cryptocurrency deposit at date t. The sample is a grid identified by *Event*, *Id*, and *Date* and spans from 3 days before the event to 3 days after. *Event* is a dummy variable marking the days when a celebrity tweet occurred. *DOW* stands for day-of-the-week fixed effects and *CS* stands for credit score. The sample is a random 50% of all data. Standard errors are clustered at the individual and date level and reported in parentheses. *** 1%, ** 5%, * 10% significance level.

Table 10: Extensive margin model

	All investments		Extensive margin		Intensive margin	
	(1)	(2)	(3)	(4)	(5)	(6)
Event-3		-0.0001		0.0001		-0.0002
		(0.0004)		(0.0001)		(0.0003)
Event-2		0.0002		0.0001		0.0001
		(0.0004)		(0.0001)		(0.0003)
Event	0.0024***	0.0025***	0.0003***	0.0004***	0.0021***	0.0021***
	(0.0005)	(0.0005)	(0.0001)	(0.0001)	(0.0004)	(0.0004)
Event+1		-0.0001		0.0002**		-0.0004
		(0.0005)		(0.0001)		(0.0004)
Event+2		0.0005		0.0003**		0.0002
		(0.0005)		(0.0001)		(0.0004)
Event+3		-0.0000		0.0001		-0.0001
		(0.0005)		(0.0001)		(0.0004)
Event FE	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y
Day of week FE	Y	Y	Y	Y	Y	Y
Tweet in Pre/Post FEs	Y	Y	Y	Y	Y	Y
Individual FE	Y	Y	Y	Y	Y	Y
N. observations	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231
N. clusters indiv.	7,952	7,952	7,952	7,952	7,952	7,952
N. clusters date	612	612	612	612	612	612
R^2	0.134	0.134	0.005	0.005	0.147	0.147
Outcome mean	0.0256	0.0256	0.0027	0.0027	0.0229	0.0229
Outcome SD	0.1580	0.1580	0.0520	0.0520	0.1496	0.1496

This table presents the results of event study regressions split by extensive and intensive margin. The dependent variable is $Deposit_{i,t}$ which takes value 1 if a user i made a cryptocurrency deposit at 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. The sample is a grid identified by *Event*, *Id*, and *Date* and spans from 3 days before the event to 3 days after. *Event* is a dummy variable marking the days when a celebrity tweet occurred. *DOW* stands for day-of-the-week fixed effects and *CS* stands for credit score. The sample is a random 50% of all data. Standard errors are clustered at the individual and date level and reported in parentheses. *** 1%, ** 5%, * 10% significance level.

Table 11: Coin summary statistics - tweets

	N events	N tweets (mean)	N tweets (p25)	N tweets (p50)	N tweets (p75)
Cardano(ADA)	13	2.3	1	1	2
Ava(AVA)	16	1.9	1	1	2
Bitcoin(BTC)	443	2.1	1	1	2
DogeCoin(DOGE)	135	2.3	1	2	3
Ether(ETH)	143	2.1	1	1	2
Luna(LUNA)	8	1.9	1	1	2
SafeMoon(SAFEMOON)	32	2.3	1	2	3
Shiba Inu (SHIB)	57	2.0	1	1	2
Solana(SOL)	11	1.5	1	1	2
Uniswap(UNI)	3	1.9	1	1	2
Axie Infinity (AXS)	13	1.7	1	1	2
Polygon(MATIC)	14	1.7	1	1	2
Tron(TRX)	19	2.1	1	1	2
Ripple(XRP)	47	2.3	1	1	3

Note: N events refers to the number of days with a tweet for each coin in the sample.

Table 12: Event Study Estimates

	All		Bitcoin		Ether		Doge		Others	
	(1) Return	(2) Volume	(3) Return	(4) Volume	(5) Return	(6) Volume	(7) Return	(8) Volume	(9) Return	(10) Volume
Days relative to tweet:										
-6	-0.005	0.005	0.003	0.003	0.007	-0.003	-0.001	0.021	-0.026	0.002
	(0.007)	(0.016)	(0.003)	(0.014)	(0.007)	(0.029)	(0.015)	(0.059)	(0.027)	(0.048)
-5	-0.004	-0.003	0.000	-0.006	0.004	-0.004	-0.002	-0.005	-0.015	0.003
	(0.006)	(0.012)	(0.003)	(0.012)	(0.007)	(0.023)	(0.018)	(0.042)	(0.020)	(0.034)
-4 (omitted)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
-3	0.006	0.008	0.001	0.002	0.007	0.014	0.022	0.004	0.008	0.026
	(0.008)	(0.013)	(0.003)	(0.013)	(0.007)	(0.019)	(0.030)	(0.053)	(0.024)	(0.034)
-2	0.011	0.027	-0.001	0.012	0.001	-0.015	0.026	0.028	0.031	0.077
	(0.009)	(0.018)	(0.003)	(0.015)	(0.007)	(0.024)	(0.029)	(0.074)	(0.030)	(0.047)
-1	0.004	0.048**	0.001	0.021	0.006	0.033	0.025	0.133	0.006	0.080
	(0.008)	(0.019)	(0.003)	(0.016)	(0.007)	(0.031)	(0.028)	(0.081)	(0.027)	(0.052)
0	0.036***	0.165***	0.001	0.058***	0.003	0.086***	0.100***	0.547***	0.092*	0.199***
	(0.013)	(0.024)	(0.003)	(0.018)	(0.008)	(0.032)	(0.031)	(0.103)	(0.050)	(0.060)
1	0.001	0.097***	0.000	0.039**	0.000	0.055	0.016	0.221**	0.001	0.153**
	(0.006)	(0.024)	(0.003)	(0.019)	(0.008)	(0.036)	(0.018)	(0.098)	(0.020)	(0.061)
2	-0.001	0.094***	0.001	0.032*	-0.001	0.052	0.019	0.215**	-0.014	0.150**
	(0.007)	(0.023)	(0.003)	(0.019)	(0.007)	(0.034)	(0.027)	(0.098)	(0.021)	(0.060)
3	0.013	0.079***	0.002	0.009	0.002	0.052*	0.008	0.232**	0.044	0.140**
	(0.012)	(0.023)	(0.003)	(0.018)	(0.006)	(0.030)	(0.016)	(0.103)	(0.046)	(0.059)
4	0.009	0.083***	-0.001	0.026	0.002	0.030	0.028	0.228**	0.024	0.134**
	(0.012)	(0.023)	(0.003)	(0.019)	(0.007)	(0.029)	(0.028)	(0.105)	(0.046)	(0.058)
5	-0.001	0.072***	0.000	0.021	-0.001	0.009	0.012	0.216**	-0.004	0.114**
	(0.005)	(0.023)	(0.003)	(0.019)	(0.007)	(0.029)	(0.017)	(0.107)	(0.019)	(0.057)
6	0.003	0.061***	-0.000	0.017	-0.000	0.011	-0.003	0.184*	0.025	0.104*
	(0.008)	(0.023)	(0.003)	(0.019)	(0.006)	(0.030)	(0.017)	(0.103)	(0.031)	(0.057)
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Tweet in Pre/Post FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	12,297	12,307	5,694	5,694	1,857	1,858	1,745	1,745	3,001	3,010
N. clusters	948	948	438	438	143	143	135	135	232	232
R^2	0.12	0.98	0.10	0.99	0.10	0.98	0.15	0.92	0.13	0.97
Outcome mean	0.01	22.29	0.00	23.66	0.00	23.17	0.03	21.09	0.03	19.83
Outcome SD	0.22	2.82	0.04	1.93	0.06	1.77	0.25	2.27	0.39	3.12

Note: Column headers identify which cryptocurrencies are included in each regression sample and the dependent variable: returns or log trading volume. Standard errors in parentheses are clustered by event. *** 1%, ** 5%, * 10% significance level.

Table 13: Difference in Differences estimates

	All		Bitcoin		Ether		Doge		Others	
	(1) Return	(2) Volume	(3) Return	(4) Volume	(5) Return	(6) Volume	(7) Return	(8) Volume	(9) Return	(10) Volume
Days relative to tweet × treat:										
-6	-0.001	0.026*	-0.004	0.013	0.004	0.002	0.007	0.041	-0.001	0.075
	(0.004)	(0.015)	(0.003)	(0.012)	(0.004)	(0.028)	(0.011)	(0.066)	(0.016)	(0.048)
-5	-0.001	0.020*	-0.002	0.001	0.003	0.012	0.016	0.064	-0.010	0.057
	(0.004)	(0.012)	(0.003)	(0.009)	(0.004)	(0.019)	(0.018)	(0.049)	(0.012)	(0.039)
-4 (omitted)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
-3	0.003	0.001	-0.002	0.008	0.006	0.004	0.008	-0.030	0.010	0.009
	(0.004)	(0.012)	(0.003)	(0.011)	(0.004)	(0.018)	(0.011)	(0.054)	(0.013)	(0.040)
-2	0.005	0.001	-0.001	-0.005	0.000	0.005	0.004	-0.109	0.021	0.055
	(0.004)	(0.017)	(0.003)	(0.013)	(0.004)	(0.026)	(0.009)	(0.069)	(0.016)	(0.050)
-1	0.010**	0.019	-0.001	-0.007	0.009**	0.041	0.017*	-0.012	0.034*	0.068
	(0.005)	(0.017)	(0.003)	(0.013)	(0.004)	(0.027)	(0.010)	(0.079)	(0.017)	(0.050)
0	0.030**	0.098***	-0.004	0.013	0.001	0.047*	0.051***	0.355***	0.112*	0.178***
	(0.014)	(0.022)	(0.003)	(0.016)	(0.005)	(0.028)	(0.015)	(0.110)	(0.063)	(0.061)
1	0.003	0.054**	-0.001	0.018	-0.000	0.030	-0.004	0.069	0.016	0.131**
	(0.004)	(0.023)	(0.003)	(0.017)	(0.007)	(0.033)	(0.011)	(0.107)	(0.012)	(0.060)
2	0.001	0.046**	-0.004	0.020	0.002	0.032	0.004	0.019	0.006	0.106*
	(0.004)	(0.023)	(0.003)	(0.019)	(0.004)	(0.035)	(0.010)	(0.106)	(0.014)	(0.061)
3	0.020	0.022	-0.002	0.006	-0.007	0.004	0.002	-0.003	0.096	0.075
	(0.016)	(0.024)	(0.003)	(0.020)	(0.007)	(0.041)	(0.011)	(0.106)	(0.070)	(0.063)
4	-0.001	0.020	-0.004	0.001	-0.001	-0.026	0.006	0.015	0.000	0.091
	(0.003)	(0.025)	(0.003)	(0.021)	(0.005)	(0.042)	(0.012)	(0.103)	(0.011)	(0.064)
5	-0.003	-0.003	-0.006*	-0.000	-0.000	-0.022	0.000	-0.044	-0.002	0.025
	(0.003)	(0.024)	(0.003)	(0.021)	(0.005)	(0.041)	(0.011)	(0.105)	(0.011)	(0.063)
6	0.007	-0.018	-0.004	-0.005	0.003	0.012	0.003	-0.111	0.036	-0.019
	(0.009)	(0.025)	(0.003)	(0.022)	(0.005)	(0.043)	(0.013)	(0.100)	(0.038)	(0.067)
Event FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Day of Week FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Tweet in Pre/Post FEs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Coin FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	44,918	44,927	23,018	23,018	7,094	7,095	4,831	4,831	9,975	9,983
N. clusters	674	674	330	330	112	112	79	79	153	153
R^2	0.07	0.96	0.06	0.97	0.10	0.96	0.09	0.93	0.08	0.95
Outcome mean	0.00	20.93	0.00	21.00	0.00	21.13	0.01	21.00	0.00	20.62
Outcome SD	0.10	2.23	0.06	2.37	0.06	2.07	0.07	1.75	0.17	2.18

Note: Column headers identify which cryptocurrencies are included in each regression sample and the dependent variable: returns or log trading volume. Standard errors in parentheses are clustered by event. *** 1%, ** 5%, * 10% significance level.

Table 14: StockTwits Finfluencers and Stocks

	Abret × 100 (1)	Abret t+1 × 100 (2)	CAR 2-5 × 100 (3)	CAR 2-30 × 100 (4)	Ret OI × 100 (5)	Ab Log Vol (6)	Frac Ret × 100 (7)
Sentiment Finf (z)	0.708***	0.056***	-0.004	0.069	0.247***		
	(0.018)	(0.008)	(0.015)	(0.053)	(0.032)		
Num Messages Finf (z)	0.361***	-0.006	-0.044**	-0.081**	0.358***	0.137***	0.093***
	(0.063)	(0.016)	(0.019)	(0.039)	(0.061)	(0.021)	(0.025)
DJNW Coverage	0.043***	0.002	0.035	0.072	0.312***	0.060***	-0.402***
	(0.009)	(0.011)	(0.027)	(0.106)	(0.070)	(0.003)	(0.065)
WSJ/NYT Coverage	-0.070***	0.001	0.103*	0.186	-0.237	0.054***	0.228***
	(0.021)	(0.023)	(0.059)	(0.168)	(0.150)	(0.008)	(0.080)
Controls	Y	Y	Y	Y	Y	Y	Y
Date & Firm FEs	Y	Y	Y	Y	Y	Y	Y
Missing Sent. FE	Y	Y	Y	Y	Y	Y	Y
Outcome Mean	-0.066	-0.065	-0.066	-0.066	-1.555	0.055	14.339
Outcome SD	3.708	3.707	3.708	3.708	34.038	0.919	12.479
Observations	3,200,760	3,199,228	3,202,253	3,202,253	2,950,496	3,154,037	2,947,969
R2	0.060	0.021	0.032	0.065	0.015	0.521	0.509

A Finfluencer is defined as being in the top 250 contributors to StockTwits, in prior calendar month, by the number of followers. The data goes from January 2013 - December 2021. All returns are scaled by 100, for readability. We focus on the top 1,500 most tweeted about stocks on StockTwits between 2010-2021. *Sentiment Finf (z)* is the average sentiment of messages posted by Finfluncers, and *Num Messages Finf (z)* is the number of messages posted by Finfluencers, about a given stock i on day t. We standardize all variables denoted with *(z)* to have mean 0 and standard deviation 1. *R*et OI is the difference between retail buying and selling volume, divided by the overall retail trading volume. *Ab Log Vol* is log turnover on day t minus average log turnover on days t-20 to t-140. *DJNW Coverage* are dummy variable equal to 1 if firm i was covered after the market closed on day $t-1$ (4:00pm) and before the market opened on day t (9:30am) on TV or DJNW, respectively. *WSJ/NYT Coverage* is a dummy variable equal to 1 if firm i was covered wither by the WSJ or the NYT on day t. Controls include one lag of the dependent variable and five lags of sentiment/number of messages (from $t-1$ to $t-5$), lagged return volatility ($t-1$ to $t-30$), lagged cumulative abnormal returns (CAR $t-1$ to $t-5$ and CAR $t-6$ to $t-30$), and lagged mean log volume (from $t-1$ to $t-30$). All regressions include crypto, date fixed effects, and a fixed effect for missing sentiment due to no posted messages about the asset that day. Standard errors are clustered at the firm and date level and reported in parentheses. *** 1%, ** 5%, * 10% significance level.

Table 15: StockTwits Finfluencers and Cryptos

Panel A: All Cryptos

	Ret × 100 (1)	Ret t+1 × 100 (2)	CR 2-5 × 100 (3)	CR 2-30 × 100 (4)	AbLogVol (5)	AbLogVol(t+1) (6)
Sentiment Finf (z)	0.050	0.005	0.119	0.454		
	(0.255)	(0.141)	(0.296)	(0.944)		
Num Messages Finf (z)	0.994	0.111	0.253	0.467	0.019	0.008
	(0.642)	(0.090)	(0.259)	(0.340)	(0.015)	(0.005)
Controls	Y	Y	Y	Y	Y	Y
Missing Sent. FE	Y	Y	Y	Y	Y	Y
Date & Coin FEs	Y	Y	Y	Y	Y	Y
Outcome Mean	1.133	0.916	3.570	25.242	0.136	0.137
Outcome SD	46.683	30.442	59.521	220.775	1.187	1.186
Observations	27,247	27,220	27,101	27,185	26,356	26,331
R2	0.105	0.122	0.257	0.537	0.530	0.878

Panel B: BTC and ETH

	Ret × 100 (1)	Ret t+1 × 100 (2)	CR 2-5 × 100 (3)	CR 2-30 × 100 (4)	AbLogVol (5)	AbLogVol(t+1) (6)
Sentiment Finf (z)	-0.014	0.080	0.219	-0.638		
	(0.067)	(0.076)	(0.177)	(0.527)		
Num Messages Finf (z)	0.262*	0.048	-0.079	0.094	0.005	0.001
	(0.041)	(0.048)	(0.070)	(0.209)	(0.002)	(0.001)
Controls	Y	Y	Y	Y	Y	Y
Missing Sent. FE	Y	Y	Y	Y	Y	Y
Date & Coin FEs	Y	Y	Y	Y	Y	Y
Outcome Mean	0.319	0.317	1.281	9.344	0.223	0.223
Outcome SD	4.792	4.790	9.799	31.134	0.741	0.741
Observations	5,770	5,766	5,746	5,762	5,640	5,636
R2	0.775	0.773	0.751	0.783	0.907	0.974

A Finfluencer is defined as being in the top 100 contributors to StockTwits, in prior calendar month, by the number of followers. The data goes from January 2018 - December 2021. In Panel A, we look at BTC, ETH, DOGE, XRP, SHIB, LUNA, ADA, SAFEMOON, UNI, AXS, AVA, TRX, MATIC, and SOL. In Panel B we focus on the big coins: BTC and ETH, and in Panel C we focus on the other coins. All returns are scaled by 100, for readability. *Sentiment Finf (z)* is the average sentiment of messages posted by Finfluencers, and *Num Messages Finf (z)* is the number of messages posted by Finfluencers, about a given stock i on day t. We standardize all variables denoted with *(z)* to have mean 0 and standard deviation 1. Controls include one lag of the dependent variable and five lags of sentiment/number of messages (from $t-1$ to $t-5$), lagged return volatility ($t-1$ to $t-30$), lagged cumulative abnormal returns (CAR $t-1$ to $t-5$ and CAR $t-6$ to $t-30$), and lagged mean log volume (from $t-1$ to $t-30$). All regressions include crypto, date fixed effects, and a fixed effect for missing sentiment due to no posted messages about the asset that day. Standard errors are clustered at the crypto and date level and reported in parentheses. *** 1%, ** 5%, * 10% significance level.

Panel C: Other Coins

	Ret × 100 (1)	Ret t+1 × 100 (2)	CR 2-5 × 100 (3)	CR 2-30 × 100 (4)	AbLogVol (5)	AbLogVol(t+1) (6)
Sentiment Finf (z)	0.296	0.046	0.084	1.058		
	(0.341)	(0.209)	(0.465)	(1.372)		
Num Messages Finf (z)	6.443**	0.921	2.812***	4.089*	0.214***	0.059***
	(2.077)	(0.734)	(0.576)	(2.029)	(0.022)	(0.014)
Controls	Y	Y	Y	Y	Y	Y
Missing Sent. FE	Y	Y	Y	Y	Y	Y
Date & Coin FEs	Y	Y	Y	Y	Y	Y
Outcome Mean	1.395	1.112	4.324	30.474	0.117	0.118
Outcome SD	53.275	34.688	67.820	251.493	1.296	1.295
Observations	20,869	20,844	20,736	20,818	20,109	20,086
R2	0.118	0.132	0.268	0.545	0.558	0.880

Online Appendix // Celebrity Influencers: *This is not Financial Advice*

Matteo Benetton, William Mullins, Marina Niessner and Jan Toczynski

Table A1: 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 A2: 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 A3: Effect of Tweets on Withdrawal Transactions [22/09]

The dependent variable is $Withdrawal_{i,t}$ which takes value 1 if a user i made an investment at date t. The sample runs from $t-3$ to $t+3$ *Event* is a dummy variable marking the days when a celebrity tweet occurred. The sample is a random 50% of all data. Standard errors are clustered at the individual and event level and reported in parentheses. Statistical significance is denoted at the ten, five, and one percent levels by *, **, and ***

	(1)	(2)	(3)	(4)	(5)	(6)
Event	0.0003***	-0.0003**	0.0003**	0.0005**	0.0004**	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)
Event × Male		0.0007***				0.0007***
		(0.0001)				(0.0001)
Event × Missing		0.0010***				0.0007***
		(0.0002)				(0.0002)
Event × Income>40k			-0.0000			0.0001
			(0.0001)			(0.0001)
Event × Income>80k			-0.0002			0.0000
			(0.0002)			(0.0002)
Event × Age>25				-0.0003		-0.0002
				(0.0002)		(0.0002)
Event × Age>35				-0.0004		-0.0002
				(0.0002)		(0.0003)
Event × CS: N/A					0.0003	0.0001
					(0.0002)	(0.0002)
Event × CS: Average					-0.0002	-0.0002
					(0.0002)	(0.0002)
Event × CS: Good					-0.0006***	-0.0006***
					(0.0002)	(0.0002)
N	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231	41,441,231
Tweet in Pre/Post FEs	Y	Y	Y	Y	Y	Y
DOW FE	Y	Y	Y	Y	Y	Y
Event FE	Y	Y	Y	Y	Y	Y
ID FE	Y	Y	Y	Y	Y	Y
N. clusters id	7,952	7,952	7,952	7,952	7,952	7,952
N. clusters date	612	612	612	612	612	612
R^2	0.042	0.042	0.042	0.042	0.042	0.042
Outcome mean	0.004	0.004	0.004	0.004	0.004	0.004
Outcome SD	0.064	0.064	0.064	0.064	0.064	0.064

Table A4: 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"}

Appendix 1. Graphs