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An Analysis of How Social Media Impacts Financial Markets

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ABSTRACT

In this paper, I examine how social media affects cryptocurrencies and more traditional stocks. I use data on Twitter posts in combination with daily stock prices to estimate the causal effect of a tweet on stock and coin prices. To do this, I use a difference-indifference regression with index funds as my control group, which allows me to capture general market trends that coins and stocks would follow if not for intervention. I find that tweets have a significant impact on cryptocurrencies that last up to three days after the post. The increase in coin prices is driven by tweets from Tyler Winklevoss and tweets about Tezos and Ethereum specifically. Meanwhile, Twitter posts have no impact on more traditional stocks. These results suggest that social media can provide the public with valuable information in real time for fast moving and volatile crypto assets, while their effects on more stable and institutionalized traditional stocks are more muted.

Introduction

Cryptocurrency is a new form of technology that promises to disrupt traditional financial systems. One can already trade, buy, and transfer these coins with users across the world without being tied down to cash. This gives finance more flexibility and adaptability to react to unforeseen technological situations and advancements, given that the coin itself is based is the internet and technology. This also provides a less institutionalized route to investing your money, thereby democratizing access to financial markets.

Since cryptocurrencies are new and innovative technologies, investors, both large and small, often have a difficult time evaluating their value and figuring out their underlying quality. This is where social media comes into play. Since these coins are extremely fast moving like the online world, social media provides a rapid route for experts to transmit information to the general public. However, social media also gives a voice to non-expert actors, with both large and small followings, who sometimes try to inflate or deflate the price of a coin of their choosing or inadvertently do so.

In this paper, I examine the impact of social media on financial markets, with a specific emphasis on cryptocurrency. I collected social media data from four different Twitter accounts mentioning cryptocurrency or traditional stocks. I then merged this social media data with financial data from Yahoo! Finance on daily stock and index prices before and after the tweet. Using this data, I ran a difference-in-difference regression to determine the causal impact of tweets on coin or stock prices. This methodology requires a control group that would in theory mirror the trajectory of the coin or stock mentioned in the tweet. I use various index funds as my control group, which allows me to capture general market trends. I then examine the difference in coin/stock prices before and after the tweet, relative to differences in index fund prices before and after the tweet. I use this methodology with several variations to test different hypotheses, including the time horizon of the effect and whether it's the same for all coins and stocks.

My results demonstrated that tweets impacted coins on a much larger scale than stocks. Although tweets had no impact on traditional stocks, tweets about coins raised coin prices by around 3% on average for at least 3 days. Lastly, one of the four users I analyzed, Tyler Winklevoss, had an unusually large impact on the stock market, as his tweets raised coin prices by 6% on average. This effect was most prevalent in Etherium and Tezos, two cryptocurrencies, while both his and other users' impact on Dogecoin was negative.

This paper proceeds as follows. Section 2 contains background information on Twitter and cryptocurrency, and my hypotheses as to why social media activity would have a larger impact on coin prices versus more established stocks. Section 3 outlines the data I use in my study. Section 4 displays my results, while Section 5 tests various mechanisms for the effect. Section 6 contains my conclusion, with suggestions for future researchers.

Background

What is Twitter?

Twitter is a social media network founded by current CEO Jack Dorsey. Users can share posts of up to 180 characters to their followers and can follow a wide variety of people, hashtags, organizations, and celebrities to receive as much information on the topics they are about. As of quarter 2 2021, Twitter has 206 million daily active users, with the majority coming from either the United States or Japan (Statista, 2021). Twitter is constantly flooded with new posts, with upwards of 350,000 tweets per minute, adding up to over 200 billion tweets per year. That is more than 25 tweets per human being on earth (Sayce, 2020). Overall, this never-ending stream of information leads users to spend around half an hour per day scrolling through their feeds (Oberlo, 2021).

Twitter and Financial News

Twitter is not just a social service; it also serves as a source of news for around 71% of its US adult consumers (Shearer and Matsa, 2018). This has led to Twitter becoming a method for influential people to disseminate information on topics of their choosing. These topics include financial markets, the focus of this paper, with the internet recommending hundreds of financial accounts to follow for investing tips and financial news. In some ways, this information is still mainstream, with organizations like CNN, CNBC, and more posting regularly, but most of these accounts are individuals who do not have a voice though traditional outlet. Twitter gives hundreds of perspectives on each situation, compared to the few from mainstream media, making it an appealing source of news for those who are interested in the market.

What is a Cryptocurrency?

According to Investopedia, "A cryptocurrency is a digital or virtual currency that is secured by cryptography, which makes it nearly impossible to counterfeit or double-spend. Many cryptocurrencies are decentralized networks based on blockchain technology—a distributed ledger enforced by a disparate network of computers" (Frankenfield, 2021). These currencies represent a large sum of monetary value, with a total market capitalization of around $2 trillion, and move hands on a constant basis (Partz, 2021). 24-hour trading volume is often over $1 trillion and almost always over $500 billion, and with trading reaching up to 50% of the entire market capitalization, these coins, while less prevalent than traditional stocks (the US stock market's market capitalization totals over 35 trillion), the daily trading volume for the US market is only about 15% of its total value (Capital, cop. 2021). This large daily change of hands leads to crypto prices being faster moving than stock prices and thus more volatile.

Why do I Think Twitter Would Have an Impact on Coin Prices but not Stock Prices?

First, why coins? The above information on volatility is confirmed when looking at Figure 1, where I display financial data from Google Finance to illustrate a comparison of some popular stocks (APPL, GS) and coins (BTC, DOGE).

This is part of the reason why I think that twitter posts would have an impact on coins. With higher volatility and more of the total value being traded at once, the price of the coin can move very quickly. It just so happens that Twitter and social media are very fast-moving news sources, with 180-character tweets coming out much faster than a two-page news article or the next day's paper. This immediate news source provides immediate information, where that information is the only news there in time for it to matter in the world of cryptocurrencies. Another reason why I believe this is similarities in demographic and timeframe between Twitter and crypto. Bitcoin, the first widely used cryptocurrency, was released in 2009, within five years of the release of Twitter (Martucci, 2021). Social media and cryptocurrency markets thus came to popularity around the same time, influencing the same group of people that were coming of age. Twitter users tend to be younger than 50 (only around 25% are older), and the average crypto trader is only 38 years old (Wojcik and Hughes, 2019, Young, 2021). Finally, I believe that cryptocurrency is more popular in modern culture, of which Twitter and other social media platforms are a hub. While traditional stocks will only be tweeted about by financial institutions and politicians, coins are posted about by celebrities and everyday people, in addition to those previously mentioned groups.

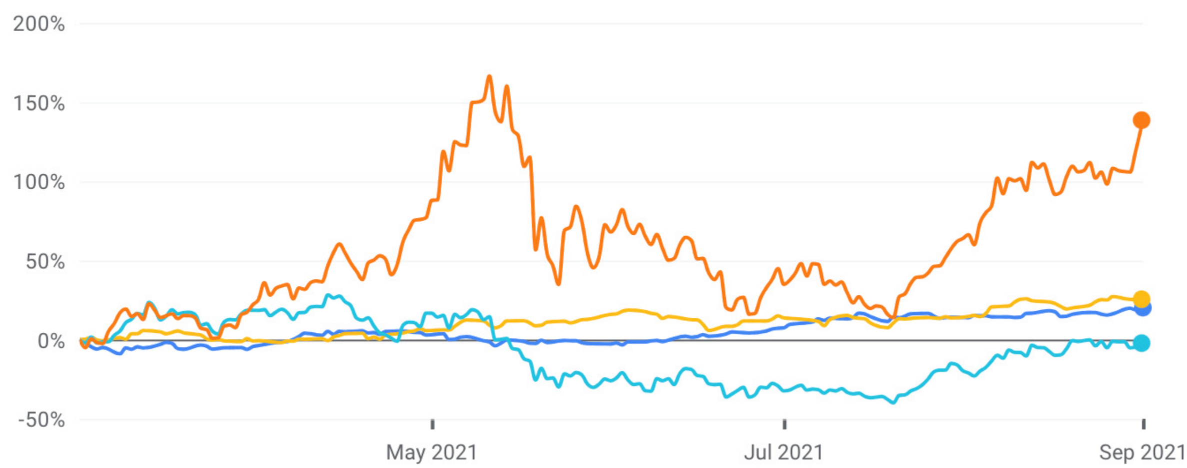

Figure 1. Price Change in Percent of APPL (Dark Blue), GS (Yellow), BTC-USD (Light Blue), and ETH-USD (Orange) over 6 Months, Ending September 1, 2021 (Google Finance, 2021).

On the other hand, why not stocks? From my research into the topic, I believe that Twitter posts would not affect traditional stock prices, the reasons mostly being the flip side of why it would affect cryptocurrencies. First, with less volatility, prices of stocks do not move nearly as quickly as coin prices do. This allows traditional media, though slower than Twitter, to react adequately and often more accurately to stocks than rapid Twitter posts, leading to a more dominant mainstream news presence where social media cannot shape price. Furthermore, the demographics line up in such a way that the average Twitter user is very dissimilar from the average stock trader. The median balance for someone in their 60's is over twenty times that of someone in their 20's, seven times that of someone in their 30's, and three times that of someone in their 40's (Knueven, 2020). Finally, while crypto has relevance in popular culture, leading to a less formal market on the whole, traditional stock markets are dominated by large institutions that are much less likely to act on a Twitter post. It is normal to see upwards of 70% of a stock owned by institutional investors, versus less than 7% of crypto (Jagerson, no date, Peterson, 2019).

Research Questions

From this information and my predictions, I developed two central research questions, each with their own sub-questions. My research questions are

Do tweets increase stock and coin prices? If so, are the results different for coins than for stocks? For how long do these impacts last?
What factors about a tweet, for example, user, sentiment, or the number of retweets, impact the change they create in stock and coin prices? Why?

Data

In order to analyze the impact of social media on stock prices, I gathered and merged data from Twitter and Yahoo! Finance. My sample consists of tweets from July 2021 from four different accounts that mentioned stocks or cryptocurrencies. To isolate the impact on a single stock or coin, I only used tweets focusing on one asset, and to stay consistent between stocks and coins, I only used prices from the weekdays (since stocks are not traded on the weekends). In selecting these accounts, I looked for variability in factors like follower count, frequency of tweets, focus on stocks or cryptocurrencies, sentiment on the market, profession, and gender; furthermore, I selected accounts that tweeted about stocks frequently enough to have multiple data points but sporadically enough to keep events independent from one another. In all, the four accounts I chose were @elonmusk, @tyler, @TMFJMo, and @AOC. Table 1 provides an overview of each account including the number of tweets used in the analysis, demonstrating frequency, and a sample tweet from each user, letting the reader know what type of tweets we are dealing with in this paper.

Table 1. Summary Statistics: Twitter Users.

Name	Account	# of Tweets	Sample Tweet Text
Elon Musk	@elonmusk	4	Baby Doge, doo, doo, doo, doo, doo, Baby Doge, doo, doo, doo, doo, doo, Baby Doge, doo, doo, doo, doo, doo, Baby Doge
Tyler Winklevoss	@tyler	7	Tez $XTZ is now available on @Gemini for trading. 👍🚀
Jason A. Moser	@TMFJMo	11	Large market opportunity ($18.5B) compared to annual revenue ($200M), profitable (WTF?), network effects, big customers in healthcare orgs, pharma, recruiting. Marketing is 80% of the biz but they're diversifying. I'll go 7 for now & give the story some time to unfold. $DOCS
Alexandria Ocasio Cortez	@AOC	4	In response to a Bezos quote thanking Amazon Employees for the Blue Origin Flight: Yes, Amazon workers did pay for this - with lower wages, union busting, a frenzied and inhumane workplace, and delivery drivers not having health insurance during a pandemic. And Amazon

			customers are paying for it with Amazon abusing their market power to hurt small business.

In these 26 tweets, 11 different stocks were mentioned along with three different cryptocurrencies. The stocks were Apple (APPL), General Electric (GE), Hasbro (HAS), PayPal (PYPL), Teladoc Health (TDOC), Docusign (DOCU), Amazon (AMZN), AppHarvest (APPH), McCormick and Company (MKS), Doximity (DOCS), and Exxon Mobil (XONA.DE), while the cryptocurrencies were Dogecoin (DOGE-USD), Etherium (ETH-USD), and Tezos (XTZ-USD). Using Yahoo Finance as a source, I collected the opening price on the day of the tweet, as well as the closing price for that day and the next two days. This allows me to capture both the short- and medium-term effect of a tweet on the stock price, and dynamically model each stocks' movement over time. The empirical strategy I will use is a difference-in-difference analysis, which requires a series of control stocks that are collected at the same time but unlikely to be affected by the tweet. My control group consists of three index funds: the Dow Jones Industrial Average (^DJI), the Russell 2000 (^RUT), and the S&P 500 (^GSPC). Table 2 provides summary statistics on the prices collected for this analysis. The Dow Jones Industrial Average Price is the highest and is almost 8 times as much as the next highest index fund. Meanwhile, the stocks and coins from our tweet sample exhibit much more volatility: the price is as low as $0.20 to as high as $3638, while the standard deviation is much higher than the others" To prevent movement in ^DJI from skewing our data and to make sure each tweet, high or low priced, is counted equally in my regression, I decided to rescale the opening day price on tweet day to 100 USD.

Table 2. Summary Statistics: Price in USD.

Variable	Mean	Standard Deviation	Minimum	Maximum
Stocks and Coin Price	474.9	970.1	0.2	3638
S&P 500 Price	4375.6	35.1	4265.1	4423.2
Dow Jones Industrial Average Price	34842.7	215.2	33981.8	35144.3
Russell 2k	2234.6	41.3	2131.8	2329.4

In addition to collecting stock prices before and after the tweet, I also gathered additional information from each tweet to use as controls in my regression. These covariates include followers, likes, retweets, and whether the tweet mentioned a stock or a coin. These covariates help increase statistical precision in my estimates of the impact of a tweet on stock prices. Table 3 provides the summary statistics for key covariates. Since I looked at accounts of various sizes, covariates such as followers, retweets, and likes display high variability, with the standard deviation in followers being greater than twenty million. Furthermore, many of the covariates displayed low variability, but that was because the options ranged between 0.0 and 1.0, in some cases those being the only two options.

Table 3. Summary Statistics: Tweets.

Variable	Mean	Standard Deviation	Minimum	Maximum
Followers	11288646.2	21267785.2	45300	59100000
Retweets	8671.9	17715	0	71600
Likes	57815.7	107107.4	8	323900
Coin? (1 if coin, 0 if stock)	0.4	0.5	0	1
Time (% of the day that had passed)	0.5	0.2	0	0.9

Retweet? (1 if a retweet, 0 if not)	0.1	0.3	0	1
Negative Sentiment? (1 if negative, 0 if not)	0.3	0.5	0	1
Weekend? (1 if date was a weekend, 0 if date was a weekday)	0.1	0.3	0	1

Empirical Strategy

My goal is to estimate the causal effects of a tweet on stock or coin prices. To do this, I used a difference-in-difference regression using Microsoft Excel. This allows me to look at a treatment and control group and calculate the effect the treatment (tweet) has on price, while taking into account the price change of a control group which was not tweeted about. For this control group, I chose to use the three indexes mentioned earlier, since they capture general market trends that could be alternate causes for changes in stock price. With the combination of accounting for covariates and changes to our control, I can use this model to accurately assess the effect of the tweet itself on price. My difference-in-difference regression takes this form:

Equation 1: $$StockPrice_{s,i} = \beta_0 + \beta_1 * Coin_s + \beta_2 * Post_t + \beta_3 * Coin_s * Post_t + \alpha * X_s + u_{s,t}$$

where *s* indexes stocks, *t* indexes time, and *X* is a matrix of control variables including number of followers, likes, retweets, tweet time, whether the tweet was on a weekend, whether the tweet was a retweet, and whether the tweet expressed negative sentiment on the stock, and u is the error term which accounts for differences between our study and the entire population. β_0, β_1, β_2, and β_3 capture the price of the control group before treatment occurs, the difference between the pretreatment averages of the treatment and control groups, the control group's increase after treatment, and the difference between the increases in price after treatment of the treatment and control groups, respectfully. I am especially interested in β_3, as it represents the causal impact of a tweet on coin/tech stock prices relative to the control group of index funds. This interpretation of β_3 relies on a standard "parallel trends" assumption in the difference-in-difference framework. That is, we must assume that with the absence of a tweet, the treatment group (stock prices) would follow the trends of the control group (index funds). With the former following and the latter capturing general market trends, this assumption logically stands.

I will run this regression in various forms. These include an aggregate model with both coins and stocks for all three time periods, one separated by time period, another that divided the tweets into coins and stocks, and a last one segregated by user. This will allow me to understand the mechanisms through which a tweet impacts stock price. In the regression tables that follow, I use *** to capture p<0.01, ** for p<0.05, and * for p<0.10.

Results

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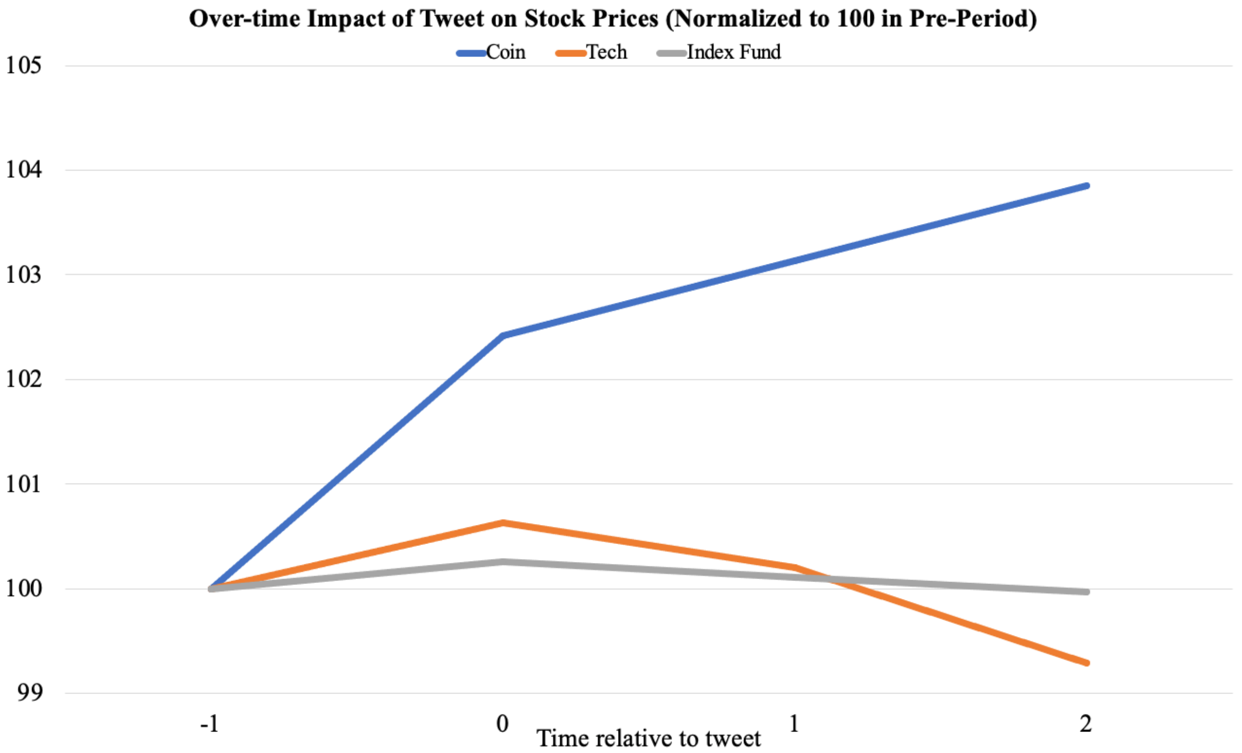

Figure 2. Average Stock Price Before and After Tweet.

To start off my results, Figure 2 displays a visual representation of my difference-in-difference model. Because of my normalization, the average price of each of the groups begins at 100. At the end of the day of the tweet, one can see that while the average price of indexes (the control) and stocks stayed within one percentage point of the original, the price of cryptocurrencies increased almost 2.5% on average. Looking further, both the average control and stock prices stay within a percentage point of the original and each other for the duration of the data, while by the end of day three, the price of coins was on average around four percent higher than both the original and the control. Overall, the graph demonstrates how tweets had a major effect on coin prices over multiple days, even when looking at them in the context of greater market trends.

My regression results confirm that tweets increase stock prices, though there is some variability in my estimates. Table 4 displays the results of equation 1 for all prices and time periods in my sample, with additional controls for tweet-level covariates. In the aggregate regression, the coefficient on coin/stock * post demonstrates that on average, tweets moved prices up around 1.1% across the first three days. However, the high standard error illustrates that on average, the results were varied enough that that finding could not be considered statistically significant at conventional levels (p=0.18). This regression returns the average impact across three days, but the large standard error may indicate there is heterogeneity in the impact across time.

Table 4. Aggregate Impact of Tweets on Stock and Coin Price, 3-Day Average.

Change in stock price	
Variable	(1)
Tweet Time	-2.89
	[0.01]***

Followers	-8.11E-08
	[3.35E-08]**
Retweets	-9.41E-05
	[5.56E-05]*
Likes	2.22E-05
	[1.39E-05]
Weekend	0.52
	[0.72]
Negative Sentiment	0.6
	[0.4]
Retweet	0.49
	[0.63]
Coin/Stock	0.00
	[0.73]
Post	0.11
	[0.42]
Coin/Stock * Post	1.12
	[0.84]
Constant	101.76
	[0.72]***
Type	Aggregate
Observations	416
R^2	0.06

Looking at my regression separated by day, the above hypothesis holds true; tweets have a causal impact on stock and coin price over the course of one day. The results of equation 1 for all prices separated by time period are displayed in Table 5 below. Over one day, the coefficient on coin/stock * post was 1.06, signifying that tweets increased prices by about 1.06%. Furthermore, though the increase in price was higher for the 2-Day and 3-Day regressions, estimates from these time windows display higher variability, shown in a higher standard error. These results suggest that while tweets increased stock prices up to 3 days afterward, the effect is only statistically significant on the first day.

Table 5. Impact of Tweets on Stock and Coin Price, Separated into 1-Day, 2-Day, and 3-Day Averages.

	Change in stock price		
Variable	(1)	(2)	(3)
Coin/Stock	0.00	0.00	0.00
	[0.41]	[0.57]	[0.73]
Post	0.25	0.18	0.11

	[0.29]	[0.35]	[0.42]
Coin/Stock * Post	1.06	1.14	1.12
	[0.58]*	[0.69]	[0.84]
Constant	100.58	101.44	101.76
	[0.53]***	[0.63]***	[0.72]***
Type	1 Day	2 Day	3 Day (Aggregate)
Observations	208	312	416
R^2	0.07	0.07	0.06

Additionally, my graph and the variability of my aggregate regression led me to believe that there may be certain subgroups where tweets have a large impact on prices and others where there is none. I was especially interested in the difference between stocks and cryptocurrencies, as the latter are a nascent industry while the former are large, established firms. Below, Table 6 displays the regression results of equation 1 by subsetting the sample for coins (column 1) and only stocks (column 2). These results indicate that tweets had a significant causal effect on cryptocurrencies, while they had little to no impact on stocks. The coefficients on coin/stock * post for each group display that tweets moved coin prices up around 3%, while stock prices stayed nearly stagnant. To boot, even though the variability for cryptocurrencies was very large with a massive standard error for coin price increase, the 3% increase was big enough to be a significant finding. However, like in the aggregate regression, this model displays the average three-day impact, but great variability may mean that the impact across time is not uniform, again similar to the aggregate.

Table 6. Impact of Tweets on Stock Price Only and Coin Price Only.

	Change in stock price	
Variable	(1)	(2)
Coin	0.00	0.00
	[1.52]	[0.62]
Post	0.20	0.06
	[0.88]	[0.36]
Coin/Stock * Post	2.94	-0.02
	[1.76]*	[0.72]
Constant	103.09	102.15
	[1.59]***	[0.79]***
Type	Coin	Stock
Observations	160	256
R^2	0.17	0.07

Once again, my regression confirmed my suspicions, with the trends looking nearly identical to the aggregate model separated by time. Table 7 shows the results of equation 1 for only cryptocurrencies separated by time period.

Though the coefficients on coin/stock * post are always above 2.00 and are all significant, lower variability, seen as a smaller standard error, leads the day 1 results to have a p-value less than 0.05. These results mirror those of the time-separated aggregate regression, in the way that day 1 results were more significant than others due to low variance.

Table 7. Impact of Tweets Coin Price only, Separated into 1-Day, 2-Day, and 3-Day Averages.

	Change in stock price		
Variable	(1)	(2)	(3)
Coin	0.00	0.00	0.00
	[0.73]	[1.13]	[0.91]
Post	0.30	0.21	0.20
	[0.52]	[0.69]	[0.91]
Coin* Post	2.12	2.57	2.94
	[1.03]**	[1.38]*	[1.82]*
Constant	100.00	100	100
	[0.36]***	[0.57]***	[0.79]***
Type	1 Day	2 Day	3 Day (Aggregate)
Observations	80	120	160
R^2	0.14	0.10	0.07

Finally, I ran a regression separating the results by time period and by twitter account, with extremely surprising results. In Table 8, I ran separate regressions for each twitter account in my sample (across the various time windows). The results indicate that Tyler Winklevoss had the largest positive impact on each day with his tweets pushing stocks up over 6% by the third day. Both of the accounts that tweet about stocks never have positive or negative impacts greater than a percentage point, but Elon Musk, often tweeting about cryptocurrency, has a large negative impact of over 3% by the third day. Overall, this may be a source of the high variability, observed in the standard error, of coin only regressions.

Table 8. Impact of Tweets on Stock and Coin Price, Separated by User and Time Period.

Twitter account	# of Tweets	Average 1 day impact	Average 2 day impact	Average aggregate impact
Alexandria Ocasio-Cortez	4	-0.76	-0.97	-0.94
Elon Musk	4	-0.93	-1.69	-2.80
Jason A. Moser	11	0.74	0.60	0.17
Tyler Winklevoss	7	3.75	4.82	6.02

Overall, my results indicate that while tweets on average increase coin and stock prices, they only have a significant impact on coins, leading to large variation in our sample. These effects are strongest on day one but are still present up to three days later. Moreover, they are driven by tweets from Tyler Winklevoss, though Elon Musk's tweets did drive prices down 2.8% over three days. These results raise questions on why Tyler Winklevoss' tweets raise prices so much more than the others in my sample.

Potential mechanisms

There are a number of potential reasons why Tyler Winklevoss has such a great impact on coin prices compared to others in my sample. In this section, I will list potential reasons and examine their feasibility as potential explanations. To assist in this process, I display Table 9, which includes the coefficients on coin/stock * post for coin tweets, separated by user, time period, and cryptocurrency.

The first possible explanation is that Tyler Winklevoss only tweets about coins, which overall were significantly impacted by tweets. However, this is not the reason for Winklevoss's success: Elon Musk also only tweets about coins, and yet Table 8 shows that Musk tweets lower stock prices while Winklevoss' raise them.

A second potential mechanism is that Tyler Winklevoss always tweets positively about cryptocurrencies, while others in the sample tweet negatively. The tweet sentiment may thus be driving the effects documented. However, this explanation is also unlikely, since users like Jason A. Moser and Elon Musk also tweet positively about stocks and coins, yet they do not drive prices up.

Third, Tyler Winklevoss tweets about smaller coins, which may be more likely to be impacted by publicity. This explanation does hold some weight: Table 9 shows that when referencing popular coins such as DOGE-USD, Winklevoss actually has a large negative impact that is similar to Elon Musk. When tweeting about other coins, however, he has a strong positive impact.

Fourth, and building upon explanation 3, now shown as feasible, Tyler Winklevoss owns a trading platform for coins, named Gemini. His tweets mentioning XTZ-USD were also tweets announcing that users could trade the coin on his platform. This is a very strong explanation for why his tweets about XTZ-USD moved up the price an average of about 14% after three days, as his tweets would coincide with more people both learning about the coin but also trading the coin on his platform. This mechanism is most likely the case for XTZ-USD, but there are still possible reasons for why tweets about ETH-USD increased prices so much.

Fifth, and also very likely, is that he is very knowledgeable about cryptocurrency, letting him predict which coins will grow, in turn giving him the trust of larger and more influential crypto investors. He owns a trading platform, giving him access to a lot of trading data from which to find trends and make predictions, and is estimated to hold $1.4 billion in coins himself. If there were anybody's word to trust when dealing with cryptocurrency, it would be Tyler Winklevoss, and I predict that most investors know that.

Table 9. Impact of Tweets by Tyler Winklevoss and Elon Musk on Coin Price, Separated by User, Time Period, and Coin.

	Winklevoss				**Elon Musk**		
Coin	**Average 1 day impact**	**Average 2 day impact**	**Average aggregate impact**		**Average 1 day impact**	**Average 2 day impact**	**Average aggregate impact**
DOGE-USD	-2.78	-3.11	-4.18		-1.67	-2.70	-4.2
ETH-USD	5.58	6.22	7.45				
XTZ-USD	7.53	10.67	14.06				

Conclusion

In this paper, I explore the impact of tweets on the price of stocks and coins. I collected data from Twitter and Yahoo finance and a difference-in-difference methodology to examine the price trajectory of coins and stocks before and after a tweet. I found that these tweets have a much larger impact on coins than stocks, on which the impact is near zero. Furthermore, the effects on coins persist at least 3 days after the tweet, raising the average price by almost 3%. Lastly, I found that one user in particular, Tyler Winklevoss, had an abnormally large impact on the stock market, his tweets raising prices by an average of 6%. This effect was concentrated in two coins specifically, Ethereum and Tezos, while he and other users all had a negative impact on the price of Dogecoin.

These results suggest that the impact of a tweet is due to an interaction effect between the sender and the coin they mention. Highly respected individuals like Winklevoss have the confidence of investors, who are likely to respond positively to their tweets. However, investors are also cognizant of the quality of coins. For that reason, the market shows the same negative impact for Dogecoin tweets regardless of whether Winklevoss or Musk tweets about it. Instead, it requires that reputable sources like Winklevoss tweet about high-quality coins to generate a positive impact.

Although this paper generates new insights on how social media activity impacts stock prices, it suffers from a few limitations. Some drawbacks to our data set included a limited time frame (only one month), a small pool of Twitter users, and only looking at one social media source. These contribute to a small sample size on the whole and an issue when trying to frame this paper as covering all of social media. For example, there may be specific characteristics of Twitter that make it more or less influential to financial markets. Additionally, the four Twitter accounts I chose may not be representative of the group of all twitter accounts that people follow for financial advice. Furthermore, there were a few limitations to my empirical strategy, mostly in the selection of control groups. Although I used index funds as my control group, a more appropriate control group for coins in specific that mirrors the trajectory of coins may have been a coin index fund. Moreover, some coins such as dogecoin were on a downward trajectory the entire month following an abnormal high, meaning they were not following general market trends anyway, breaking the parallel trends assumption required in a difference-in-difference model. This also highlights the time frame limitation.

The results in this paper open up a variety of interesting questions for future researchers. One easy step to discovering more about the impact of these tweets on prices would be to expand the time trajectory before and after. With my research finding no time limit on the effectiveness of tweets on coin prices, a larger trajectory would help discover these breakpoints. In a similar light, future research could also narrow in on micro-level changes at the minute-by-minute mark, looking at more immediate financial reactions. Second, it would be interesting to narrow in on what specifically the tweet language is accomplishing. For example, it would be interesting to study these dynamics when multiple coins are included in a tweet, or when different accounts tweet about the same coin on the same day. New results could help investors or even investing software use specific social media posts as data points when predicting or deciding on stocks to invest, filtering useful posts out from a large pool. Finally, another interesting avenue for future research would be to look more closely at the sentiment of tweets. Recent advances in machine learning allow researchers to closely measure the emotions associated with language. Using these tools can further expand our understanding of how social media impacts markets as a whole.

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References

Capital. (2021) 'How much money is traded on the NYSE daily?,' *Capital* [Online]. Available at: https://newventuretec.com/stock-market/how-much-money-is-traded-on-the-nyse-daily.html (Accessed: 1 September 2021)

Frankenfield, J. (2021) 'Cryptocurrency,' *Investopedia* [Online]. Available at: https://www.investopedia.com/terms/c/cryptocurrency.asp (Accessed: 1 September 2021)
Partz, H. (2021) 'Total crypto market value breaks $1.9T for the first time since May,' *Cointelegraph* [Online]. Available at: https://cointelegraph.com/news/total-crypto-market-value-breaks-1-9t-for-first-time-since-may (Accessed: 1 September 2021)

Jagerson, J. 'Understanding institutional ownership,' *Learning Markets* [Online]. Available at: https://www.learningmarkets.com/understanding-institutional-ownership/ (Accessed: 1 September 2021)

Knueven, L. (2020) 'How much the typical American has invested outside of retirement accounts at every age,' *Business Insider* [Online]. Available at: https://www.businessinsider.com/personal-finance/investments-by-age-americans-non-retirement-2020-3 (Accessed: 1 September 2021)

Martucci, B. (2021) 'What is cryptocurrency? How it works, history, and Bitcoin alternatives,' *Money Crashers* [Online]. Available at: https://www.moneycrashers.com/cryptocurrency-history-bitcoin-alternatives/ (Accessed: 1 September 2021)

Oberlo. (2021) 'Average time spent on social media in 2021,' *Oberlo* [Online]. Available at: https://www.oberlo.com/statistics/average-time-spent-on-social-media (Accessed: 1 September 2021)

Peterson, C. (2019) 'Binance research report claims that less than 7% of crypto is owned by institutions,' *NEWSBTC* [Online]. Available at: https://www.newsbtc.com/news/binance-research-report-claims-that-less-than-7-of-crypto-is-owned-by-institutions/ (Accessed: 1 September 2021)

Sayce, D. (2020) *The number of tweets per day in 2020* [Online]. Available at: https://www.dsayce.com/social-media/tweets-day/ (Accessed: 1 September 2021)

Shearer, E. and Matsa, K.E. (2018) 'News use across social media platforms', *Pew Research Center* [online]. Available at: https://www.pewresearch.org/journalism/2018/09/10/news-use-across-social-media-platforms-2018/ (Accessed: 1 September 2021)

Statista. (2021) 'Number of active Twitter users in selected countries,' *Statista* [Online]. Available at: https://www.statista.com/statistics/242606/number-of-active-twitter-users-in-selected-countries/ (Accessed: 1 September 2021)

Wojcik, S. and Hughes, A. (2019) 'Sizing up Twitter users, *Pew Research Center* [online]. Available at: https://www.pewresearch.org/internet/2019/04/24/sizing-up-twitter-users/ (Accessed: 1 September 2021)

Young, E. (2019) 'More than one in ten Americans surveyed invest in cryptocurrencies,' *NORC* [Online]. Available at: https://www.norc.org/NewsEventsPublications/PressReleases/Pages/more-than-one-in-ten-americans-surveyed-invest-in-cryptocurrencies.aspx (Accessed: 1 September 2021)