# Does Partisanship Shape Investor Beliefs? Evidence from the COVID-19 Pandemic

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**Abstract**

We use party-identifying language – like "Liberal Media" and "MAGA"– to identify Republican users on the investor social platform StockTwits. Using a difference-in-difference design, we find that the beliefs of partisan Republicans about equities remain relatively unfazed during the COVID-19 pandemic, while other users become considerably more pessimistic. In cross-sectional tests, we find Republicans become relatively more *optimistic* about stocks that suffered the most from COVID-19, but more *pessimistic* about Chinese stocks. Finally, stocks with the greatest partisan disagreement on StockTwits have significantly more trading in the broader market, explaining 28% of the increase in stock turnover during the pandemic.

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# 1 Introduction

The COVID-19 pandemic presented investors with a complex valuation problem. With the first sign of community spread in the United States, investors were faced with a series of questions: How quickly would the virus spread? How deadly would it be? How would the government respond? How long would the pandemic last? How quickly would the economy recover? Could the pandemic present an *opportunity* for some firms? With fundamental uncertainty about each of these factors, even among experts, investors had to update their expectations about firms' future prospects.

In this paper, we show these investor expectations in the wake of COVID-19 can be predicted from their political identity as measured before COVID-19. Specifically, we find that partisan Republicans become more optimistic than other investors when the crisis begins and remain more optimistic through the end of April 2020. We also show that political identity shapes views among the cross-section of stocks during the pandemic: Republicans become more *pessimistic* about US-listed Chinese firms (e.g., Baidu and Alibaba) while remaining more *optimistic* about firms that experienced the greatest losses. We also find that stocks with the greatest partisan disagreement see the greatest increase in stock turnover during the COVID-19 period.

Partisan differences influence beliefs across a host of issues (Milner and Judkins, 2004; Gaines et al., 2007) and have increased dramatically in the last thirty years (Bishop, 2008; Abramowitz and Saunders, 2008; Gentzkow, Shapiro, and Taddy, 2019; Kaplan, Spenkuch, and Sullivan, 2019). It is nonetheless surprising to see partisan identity matter when forming stock expectations. Investors have a strong financial incentive to form correct beliefs about a stock's future cash flows regardless of political affiliation. If partisan identity does not help investors update expectations about a firm's prospects, then their political identity should be ignored when when forming these expectations. Nevertheless, we find a widening and sustained difference in investor beliefs between partisan Republicans and other investors beginning with the onset of the COVID-19 pandemic.

We employ novel data from StockTwits, a popular investor social network, to measure partisan identity at the individual level, and observe investment beliefs at a daily frequency. StockTwits users explicitly stamp individual messages with bullish or bearish sentiment, which gives a direct measure of their investment beliefs. We observe precisely when these declarations of sentiment are made, allowing us to track the evolution of investor beliefs through the COVID-19 pandemic. Critically, to link investor beliefs to partisanship, we observe individuals' partisan affiliation as revealed by their use of political language in StockTwits posts prior to the pandemic. Our classification, which follows an approach similar to Gentzkow and Shapiro (2010), cleanly identifies partisan Republican individuals who use the platform.[1]

We identify how partisanship shapes investor beliefs during the COVID-19 period using a difference-in-difference design. We compare the difference in optimism between Republicans and non-Republicans (the first difference) before and during the COVID-19 period in the United States (the second difference). In support of our empirical approach, we observe parallel pre-trends for investment beliefs in the pre-COVID period (e.g., Figure 4), followed by a sharp divergence in investor beliefs after the first suspected case of community spread of the virus in the United States.

Our core finding is that partisan Republicans remain, on average, more optimistic about equities than other users during the COVID-19 period. The optimism of partisan Republicans closely tracks that of other users from October 2019 through February 2020. However, after the first case of U.S. community spread of COVID-19 in late February, partisan Republicans became significantly more optimistic than other StockTwits users – a difference of 2-3 percentage points across all stocks and 4-5 percentage points for firms in the S&P500. Because we include user-security fixed effects, these estimates reflect changes in

[1] We also validate our individual classification of partisan users using belief updating around the 2016 election. Consistent with the evidence in Meeuwis et al. (2019), we find that partisan Republicans become significantly more optimistic than other StockTwits users around the 2016 election of Donald Trump. Moreover, this partisan gap in optimism rises at critical junctures during the Trump presidency: the onset of the U.S.-China trade war, the 20% market drawdown of late 2018, and the primary focus of this study, the COVID-19 crisis in the U.S.

optimism *within user* about the same security through the COVID-19 period. This partisan optimism gap held throughout the COVID crisis, as market valuations reached their bottom in late March and began to recover in April.[2]

We also perform heterogeneity tests to illuminate the underlying source of partisan investor optimism during the pandemic. First, we evaluate whether partisan Republicans became more optimistic than other users about stocks that suffered the largest losses during the COVID-19 period. Greater optimism about stocks that lost value during the crisis reflects a belief in a quick stock market recovery. Consistent with this view, our tests reveal that partisan Republicans are disproportionately more optimistic about stocks that fell the most during the COVID-19 period.

Second, we examine Republicans' relative beliefs about US-listed Chinese stocks (e.g., Baidu or Alibaba) during the COVID-19 crisis. President Trump repeatedly identified COVID-19 as the "Chinese virus" in public statements, and singled out China's lack of forthright communication about the seriousness of the virus in the early stages of the pandemic (Higgins, 2020). Consistent with politically-driven negativity about China affecting the investment beliefs of partisan Republicans, we find that they are significantly more pessimistic about Chinese stocks *during the outbreak in the United States*. The timing of Republican beliefs about Chinese stocks is instructive: they did not become more pessimistic about these stocks during the COVID-19 outbreak in China; instead, Republicans became pessimistic about them in mid-March when new cases in China had fallen, but the crisis in the U.S. was deepening. This points to a political, rather than economic, model for their beliefs.[3]

The political divide in investor beliefs during COVID-19 coincided with an enormous

[2] Our difference-in-difference design recovers the *partisan gap* in investment beliefs that emerges during the pandemic. We do not, however, take a position on whether Republicans or non-Republicans have correct beliefs during the pandemic. Our goal is to identify the role of political identity in shaping investor beliefs during the COVID-19 pandemic.

[3] Pessimism about Chinese firms could reflect the belief that Western politicians would place economic restrictions on these companies. However, according to this view, non-Republicans should also become more pessimistic about Chinese stocks. Viewed in this light, our finding of *differential* pessimism by Republicans is difficult to reconcile with purely economic beliefs.

increase in trading volume: at the height of the pandemic, abnormal daily stock turnover had increased by approximately 36% relative to pre-pandemic levels. In our final set of tests, we measure partisan disagreement at the daily stock level and relate abnormal stock turnover to partisan disagreement among the cross-section of stocks. Our estimates imply a tight connection: a one standard deviation increase in partisan disagreement during the pandemic leads to 10% more abnormal stock turnover, which is 28% of its increase during the COVID-19 period, and is greater than the trading implied by a standard deviation increase in overall disagreement.

Our analysis primarily focuses on how partisan investment beliefs diverge during the COVID-19 period, but our measure of partisan Republican sentiment accurately reflects political events outside of this period. We find that Republicans became relatively more optimistic about equities after the 2016 Presidential Election and during the US-China Trade War that began in early 2018 and culminated with a near 20% market drawdown in December 2018. These key moments of politically-based divergence in investor beliefs on StockTwits also appear in Internet search volume. Google Search Intensity for "Trump" together with "stock market" spikes for each of these events: the 2016 election, the US-China trade war and the COVID-19 pandemic. In fact, Google Search Intensity for "Trump and stock market" is greater during the COVID-19 period than around the 2016 election, suggesting that the pandemic is an especially important period to investigate partisan disagreement in investor beliefs. Moreover, the fact that these spikes in Google search volume coincide with a widening of the partisan optimism gap on Stocktwits provides support for the external validity of our partisan classification, as does our finding of a clear link between partisan disagreement and stock market turnover.[4]

Our central contribution is to show an individual link between partisan identity and investor beliefs. Our findings most closely relate to Meeuwis, Parker, Schoar, and Simester

[4]Buckman et al. (2020) provides a daily news sentiment index that extends through the COVID-19 period. In appendix Figure A.7 we find that the expectations of the majority of StockTwits users closely track this index during 2020 and for several years before (correlations of around 0.8).

(2019), which shows that individuals in Republican areas invest their retirement assets more aggressively after the 2016 election, consistent with partisan investment optimism. Our analysis of investment beliefs during the pandemic period is substantively different in at least two ways. First, the COVID-19 period was not only a shock to the level of economic activity,[5] but also a shock to uncertainty (e.g., Baker et al. 2020a) . Thus, our finding of partisan optimism in the face of the pandemic is different than showing that Republican investors view a Republican policy regime as favorable to stock market valuations, and suggests that people default to core identities, such as political affiliation, when facing significant uncertainty.[6] Second, our evidence is from direct observation of investment beliefs, expressed on StockTwits, whereas Meeuwis et al. (2019) infer differences in investment beliefs from changes to portfolio holdings.

Our research also contributes to the emerging literature on how partisan identity shapes financial beliefs (e.g., Kempf and Tsoutsoura, 2019). Our party-identification and sentiment measures from StockTwits have four advantages. First, our use of high-frequency data on belief revisions enables us to describe the partisan dynamics at a daily or weekly frequency, cleanly identifying the effect of an event on beliefs. Second, we provide an *individual* link between partisanship and direct declarations of investment beliefs rather than relying on geography to infer partisan identity. Geography is correlated with many variables besides political party while individual declarations, such as #Trump2020, are unequivocal.[7] Third, we show important *cross-sectional* differences in partisan belief formation: our finding of Republicans' pessimism about Chinese stocks shows that these partisan investor beliefs do not merely reflect general economic optimism, but a more nuanced

[5] U.S. GDP decreased at an annual rate of 32.9% in the second quarter of 2020 according to the BEA advance estimate.

[6] The uncertainty-identity theory of Hogg (2007) argues that people cling to their social identity as a way to reduce uncertainty. Relatedly, Bénabou and Tirole (2011) develop a model in which investments in one's identity (e.g., political identity) are important for shaping beliefs.

[7] Using geography to proxy for partisan identity risks conflating partisanship with other omitted factors that relate to investor belief formation, e.g., social connections (Bailey et al., 2018b). Meeuwis et al. (2019) addresses this measurement concern by ruling out hedging needs and initial differences, and use survey data to show that Republicans are more optimistic about the national economy, but not about their own economic situations.

alignment of investor beliefs with partisan philosophy. Finally, we connect these beliefs to outcomes in the overall market, specifically the extent of daily stock turnover.

Our research also relates to the literature on belief formation (Bailey et al., 2018a) and sources of disagreement (Cookson and Niessner, 2020). Our main findings suggest that partisan identity affects how people update their market beliefs upon the arrival of new public information. In showing that a non-informational factor drives differential belief updating, we provide new evidence that investors apply different models to interpret market information (e.g., Kandel and Pearson, 1995). The political friction we identify is distinct from other views about inefficient belief updating, such as extrapolation (Bordalo, Gennaioli, and Schleifer, 2018) or motivated beliefs (Brunnermeier and Parker, 2005; Benabou, 2015), and is complementary to work on selective exposure to confirmatory information (Cookson, Engelberg, and Mullins, 2020). Relative to existing work on how investors form beliefs, we show that partisan identity can lead to significant differences, which is surprising given recent evidence that typical investor characteristics do not explain much variation (Giglio et al., 2020a).[8]

A survey-based literature in political science robustly shows that people express greater optimism about the economy when their partisan position matches that of the Government (e.g., Bartels (2002) and Evans and Andersen (2006)). A related series of papers argues that this link between partisanship and economic perceptions affects outcomes such as spending or economic activity (Gerber and Huber, 2009, 2010; Gillitzer and Prasad, 2018; Benhabib and Spiegel, 2019), but recent work has challenged this claim (McGrath, 2017; Mian, Sufi, and Khoshkhou, 2017). Our paper contributes to this debate on the real effects of partisan perceptions by providing evidence that partisan disagreement materially increases stock market trading volume.

Though both political and investment beliefs have been studied in the context of COVID-

[8]Our research also relates to, but is distinct from, the literature on media slant (Gentzkow and Shapiro, 2010). Goldman, Gupta, and Israelsen (2020) show Republican firms are covered more favorably in the *Wall Street Journal* than in the *New York Times*. Political bias in media coverage may contribute to our observed differences in investor beliefs.

19, our work is the first to connect the two. For example, several articles have shown that political beliefs affect real activities such as social distancing compliance (Allcott et al., 2020; Barrios and Hochberg, 2020; Painter and Qiu, 2020) and subsequent infection rates (Burstyn et al., 2020). In addition, there is an emerging literature that has studied how COVID-19 has affected household consumption (Baker et al., 2020b), risk preferences (Bu et al., 2020), expectations (Hanspal, Weber, and Wohlfart, 2020), and belief updating (Giglio et al., 2020b). Our findings draw a connection between political and investment beliefs during COVID-19 by showing a strong divergence in stock market beliefs between Republicans and non-Republicans, and a relationship between this partisan-based disagreement and the cross-section of trading volume.

# 2 Setting and Data

In this section, we describe the StockTwits data, describe our approach to identifying partisans among StockTwits users, and provide some initial evidence linking partisanship and investor beliefs.

## 2.1 StockTwits Data on Investor Beliefs

We employ message-level data from the investor social network, StockTwits. Founded in 2008, StockTwits claims to be the "largest social network for investors and traders, with over two million registered community members and millions of monthly visitors." The platform is similar to Twitter. Panel (a) of Figure 1 shows the user interface. Users post messages of up to 1,000 characters and use "cashtags" with the stock symbol (e.g., $AAPL or $BTC for Apple or Bitcoin) to link the user's message to a particular company. Cashtags allow users to aggregate opinions about particular stocks or other assets in a broader discussion, just like hashtags on Twitter.

Although StockTwits users are not a fully representative sample of investors, the opinions expressed on StockTwits have been shown to have external reliability. For example, prior work has linked dispersion of opinion on StockTwits to overall trading volume in stocks: Both Cookson and Niessner (2020) and Giannini, Irvine, and Shu (2018) show that proxies for dispersion of sentiment relate to market-level trading volume. Because of its unique data features, such as social connections and high-frequency belief updating, profile information on location, and investor approaches, StockTwits has begun to attract academic attention (Giannini, Irvine, and Shu, 2017; Cookson, Engelberg, and Mullins, 2020).

We have the full history of messages posted to StockTwits through April 2020. We restrict attention to messages that mention only one ticker to focus on sentiment that can be directly linked to a specific stock. Panel (a) of Table 1 presents summary information on our sample. Focusing on StockTwits posts from October 2019 through April 2020, our sample contains 2.3 million user-security-day observations, (119,434 unique users) about 1,042 unique securities (stocks, indexes and other assets). Our specifications with user-security fixed effects drop singleton observations (i.e., users who post only once about a security during our sample period), leaving us with approximately 1.9 million useable observations in the October 2019 – April 2020 sample.

A valuable feature of StockTwits for academic research is that the platform encourages users to self-classify whether their sentiment is bullish or bearish for each message. Users can by click on a prominently displayed button on the StockTwits interface before posting (e.g., see Panel (a) of Figure 1). Following Cookson, Engelberg, and Mullins (2020), our observations aggregate posts to the user-stock-day level to prevent a user with multiple posts about a security on a single a day from having inordinate weightIn addition, old messages cannot be deleted on StockTwits. This feature not only preserves the incentives of users to post truthful best forecasts for their follower-base but also ensures that the data we extract from StockTwits reflect an unselected view of how users viewed the market at each date in our sample. Using a battery of analyses of text and market events, Cookson and Niessner (2020) provide extensive validation on the bullish versus bearish classification.

Panels (b) and (c) of Figure 1 present examples of a bullish post and a bearish post about Apple (symbol $AAPL).

## 2.2 Identifying Partisan Investors in StockTwits

In addition to the self-classified sentiment about investments, StockTwits users sometimes discuss other topics, including politics. These additional posts are useful for measuring individual users' partisan affiliation. We follow Gentzkow and Shapiro (2010) and identify a list of keywords that flag posts as political.

We begin by identifying partisan Republicans. The process is as follows: we consider all posts before 2020 that expressed direct support for President Trump's reelection via the terms #Trump2020 and #MAGA. For the users who created these posts, we examine all of their *other* posts, looking for terms that this group uses at least 20x more frequently than other users. From these posts, we select purely political terms that meet this condition, such as "Stupid dems" and "Leftists." Then, we identify users who employ this expanded set of terms frequently. Adding these users to our set of partisan Republicans, we identify additional political terms that this expanded group uses more frequently than other users. We continue to iterate in this way until no new political phrases emerge. We take a similar approach to identify partisan Democrats, beginning with the terms "Idiot Trump" and "Stupid Trump."

Panel (a) of Table 2 reports the final list of keywords, which contain distinctively partisan Republican or Democrat language, such as "Liberal Media" and "Russia Hoax" among Republicans, and "Faux News" and "#ImpeachTrump" among Democrats. The vast majority of the posts containing keywords are unambiguously partisan. We report several examples of partisan messages in Panel (b) of Table 2. To be clear, this classification of users is "out of sample" in two respects: (1) partisan users are identified via pre-2020 messages, distinctly prior to our COVID-19 sample period and (2) the sentiment-stamped messages in our analysis rarely contain political language. Because the classification assigns partisanship at the user level, we do not rely upon the combination of messages that contain sentiment and political statements.

Panel (b) of Table 1 presents summary information on our classification procedure. Applied to the 179.2 million StockTwits messages before 2020, a total of 70,031 messages contain partisan keywords (18,371 are stamped with bullish or bearish sentiment). Out of the 780,908 users who were active on StockTwits prior to 2020, we identify 34,284 users who make or like at least one partisan message.

For each user, we count the number of Republican ($R$) and Democrat ($D$) messages that they either posted or liked on Stocktwits before 2020. We measure each user's partisanship as the difference between the two ($R-D$). Table A.1 provides information about the number of users we observe in our sample at various levels of $R-D$.[9] The table illustrates that Stocktwits has many more Republican than Democrat users, consistent with Ke (2019). For example, we observe 5,426 users where $R-D \geq 2$ but only 323 users where $R-D \leq -2$. Because our sample contains so few identifiable Democrats, our analysis throughout compares partisan Republicans to everyone else. However, both Table A.1 and Figure A.1 illustrate that when we consider our main finding among partisan Democrats we find the opposite result: partisan Democrats become relatively more *pessimistic* during the pandemic, although this result is statistically insignificant (likely because we have so few partisan Democrat users).

For our main analysis we identify partisan Republicans as those who have an $R-D$ of at least 4. In other words, we require that, before 2020, a user has either posted or liked at least 4 messages with political sentiment and that the number of Republican messages outnumber the number of Democrat messages by at least 4. Table A.1 demonstrates that other cutoffs (e.g., $R-D \geq 3$ or $R-D \geq 5$) yield similar results. Our $R-D \geq 4$ constraint helps ensure that the individuals we identify are truly and persistently partisan Republican,

[9]The number of users reported in Table A.1, and all regression tables, is after dropping singletons generated by our user-security fixed effects, i.e., users that post no more than once about each security in the regression time period are not included in these numbers.

and identifies 6,191 users in the pre-2020 period. Restricting attention to the sample period (Oct 2019–Apr 2020), our sample contains 3,448 Republican-identified users and a comparison group of 115,986 other users who were active during this period.[10] Of course, many of these other users are also Republicans who do not regularly use or like Republican language on StockTwits. To the extent that our comparison group includes non-partisan users and some partisan Republicans missed by our classification, our estimates potentially understate the true size of the partisan gap. Finally, although partisan Republicans comprise only 3% of the users in our sample, they tend to be more active, making up 12% of the user-symbol-day level observations.

## 2.3 Describing the Politicization of Stock Markets

Since the 2016 Presidential Election, President Trump has strengthened the connection between political identity and beliefs about the stock market. He has tweeted about the "stock market" 130 times through May 24th, 2020, and often cites the rise of the stock market as a political accomplishment while cheering market milestones.[11] Meeuwis et al. (2019) highlights a connection between partisan identity and investment beliefs, showing that the 2016 Presidential Election led investors from pro-Trump zip codes to invest more aggressively, whereas investors in pro-Clinton zip codes did the opposite.

As validation of our classification of investor partisanship, we evaluate the sentiment of StockTwits messages beginning in January 2015. To construct a time series of sentiment by partisan affiliation we estimate the following specification:

$$Bull_{s,j,t} = \eta_{s,j} + \gamma^R(\mathbb{1}Month_m \times \mathbb{1}PartisanR_j) + \gamma^B \mathbb{1}Month_m + \varepsilon_{s,j,t} \tag{1}$$

in which the dependent variable is an indicator for whether user $j$ is bullish about stock

[10] Most of our regressions consider the set of securities that have a permno and drop singleton observations. With these restrictions, we have 2,754 partisan Republican and 66,634 other users.

[11] The tweets can be found at the online Trump Twitter Archive (https://bit.ly/3cBxbmN).

$s$ on day $t$, and $\eta_{s,j}$ are user-security fixed effects which absorb each user's average sentiment about each security over the sample period. $\gamma^B$ are month fixed effects for the baseline group of users who are not partisan Republicans, while the vector of fixed effects $\gamma^R$ captures the differential sentiment of partisan Republican users. These fixed effect estimates are time-varying sentiment measures, specific to how the opinions of each group – partisan Republicans versus other users – change over time.

Panel (a) of Figure 2 plots the estimated sentiment time series, obtained from equation (1). Prior to the date when Donald Trump was nominated (in July 2016), partisan Republicans and other users on StockTwits exhibit very similar sentiment patterns. Consistent with the portfolio-based observations in Meeuwis et al. (2019), we observe that the 2016 Election leads partisan Republicans to become substantially more optimistic than other users, and this divergence in investor optimism persists. Moreover, the plot shows that other important events during the Trump Presidency coincided with growth in the gap between the sentiment of partisan Republicans and other users: the onset of the US-China trade war, the market drawdown in December 2018, and the COVID period.

Beyond StockTwits, these periods of divergence of investor opinions coincide with the public drawing a connection between politics and the stock market. Panel (b) of Figure 2 presents a plot of Google Search Intensity for "Trump and Stock Market."[12] Consistent with the points of divergence we observe in Panel (a), Google Search Intensity for this pair of terms has sharp spikes around the 2016 election, the onset of the US-China trade war, the December 2018 market drawdown, and the COVID-19 period. The fact that these spikes in Google search volume coincide with our measured Republican bullishness on StockTwits also supports the external validity of our partisan Republican classification. In other words, it appears unlikely that our classification is picking up the views of an

[12] President Trump has often associated his administration with stock market performance. On February 7, 2018, he tweeted, *"In the "old days," when good news was reported, the Stock Market would go up. Today, when good news is reported, the Stock Market goes down. Big mistake, and we have so much good (great) news about the economy!"* The tweet provides supporters of the President with guidance for how to interpret news about the economy, consistent with differential interpretation of a public signal as in Kandel and Pearson (1995).

unrepresentative population; it seems more likely that they represent broader partisan views given that they coincide with the revealed interest of the Google-user population (Google had approximately 250 million users in the US in 2019).[13]

## 2.4 Partisan Investor Beliefs during COVID-19

We focus on the COVID-19 period for several reasons. First, as we saw in Panel (a) of Figure 2, the sharpest divergence of partisan investor beliefs occurs during the pandemic. Second, the COVID-19 period also exhibits the largest amount of attention to "Trump and Stock Market," indicating that the connection between politics and financial markets is particularly salient during the pandemic. Third, as we show in Section 4, the COVID-19 period exhibited significant market turmoil, with especially high trading volume. Divergence of opinion is one potential explanation for this volume increase, and, as we will show, partisan differences of opinion are an important explanation for this rise in trading.

To provide evidence on the timing of the pandemic shock, we estimate a version of equation (1), with *daily* fixed effects from January 2020 through April 2020. Panel (a) of Figure 3 presents the estimated daily sentiment fixed effects, after sweeping out user-stock fixed effects. This series shows that partisan Republicans and other users on StockTwits exhibit similar investor belief dynamics from the beginning of January through the beginning of March, but as of early March, partisan Republicans become significantly more optimistic than other users. Panel (b) shows that the divergence in beliefs corresponds closely to when Google Search volume for "Trump and Stock Market" spikes.

[13] Our finding of a strong link between partisan disagreement and stock market turnover (in Table 6) also supports the external validity of our partisanship measure. Similarly, in appendix Figure A.7 we find that the expectations of the majority of StockTwits users closely track the daily news sentiment index from Shapiro, Sudhof, and Wilson (Forthcoming) and Buckman et al. (2020) during the COVID-19 period, and for several years before (correlations of around 0.8).

# 3 Evidence of Partisan Investor Beliefs

This section presents regression evidence of how the investor beliefs of partisan Republicans diverge from other users on StockTwits through the COVID-19 period.

## 3.1 Partisan Republican Investor Optimism

We estimate the partisan gap in investor optimism during COVID-19 by focusing on the period from October 2019 through April 2020. Using the sample of user-security-day observations of sentiment-stamped declarations about single stocks, we estimate the following monthly difference-in-difference specification:

$$Bull_{s,j,t} = \eta_{s,j} + \gamma^B \mathbb{1}Month_m + \sum_m \beta_m^R (\mathbb{1}Month_m \times \mathbb{1}PartisanR_j) + \varepsilon_{s,j,t} \tag{2}$$

in which the dependent variable $Bull_{s,j,t}$ is an indicator for whether user $j$ is bullish about stock $s$ on day $t$ (multiplied by 100 to aid interpretation as a percentage). $\eta_{s,j}$ are user-security fixed effects that absorb the average sentiment of each user about each security in the sample period. The month fixed effects ($\gamma_m^B$) yield time-varying sentiment estimates for the baseline group. The coefficients of interest are $\beta_m^R$, which give the month-by-month differences of partisan Republican investor sentiment relative to that of other users. We cluster standard errors by user to account for serial correlation in sentiment within user.

Table 3 presents estimates of equation (2): column (1) is estimated for all securities (including non-stock securities like Bitcoin), column (2) restricts attention to stocks with a CRSP PERMNO , column (3) drops small capitalization stocks below the 25th percentile of NYSE market capitalization as in Fama and French (2008) ($990 million here), and column (4) restricts the sample to stocks in the S&P500 index as of Feb 29, 2020. To evaluate overall market optimism, it is not ideal to include non-stock securities (as in column 1), as these securities may reflect views of fragmented and often idiosyncratic markets. Nevertheless, regardless of the sample,we obtain qualitatively similar findings.

Consistent with the deterioration of the market after the first sign of community spread of COVID-19 in the U.S., the month fixed effect coefficients reflect a decline in optimism among the baseline category of investors, especially in March 2020. Referring to column (3), which reports the results for the sample that excludes small firms, users are almost 6 percentage points less likely to express bullish sentiment in March and April 2020 than they were in November 2019 (the reference month). Relative to this decline in baseline optimism, we estimate that partisan Republicans are 3.7 to 4 percentage points more optimistic during March and April 2020. Moreover, examining the time series of partisan Republican $\times$ month estimates, we observe similar trends in investor beliefs from October 2019 through February 2020, with a sharp divergence in March.

Figure 4 plots the estimates of the partisan Republican $\times$ month interactions from the same specification used for Table 3, but estimated on a longer pre-period from March 2019 through April 2020. Panel (a) presents the sample that excludes small capitalization stocks, and shows that the parallel pre-trends in beliefs are robust to using a longer sample. Moreover, as we highlight in Panel (b) and in column (4) of Table 3, the difference in the beliefs of partisan Republicans in the COVID-19 period is larger when we condition on large capitalization stocks in the S&P500.[14]

Republicans remaining optimistic during the pandemic might suggest that they are optimists in general, which could drive our result. To address this concern, in column (7) of appendix Table A.2 we classify the 28% of users that always declare bullish sentiment pre-2020 as "Pre-Covid Optimists." We estimate a single difference-in-differences coefficient on $\mathbb{1}Covid_t \times \mathbb{1}PartisanR_j$, rather than month-by-month coefficients (to keep the comparison simple), and add an analogous interaction for Pre-Covid Optimists. Although the Pre-Covid Optimists are indeed differentially optimistic during the pandemic, Column (7) of Table A.2 in the appendix shows that controlling for these optimists actually strengthens the estimated partisan gap between Republicans and other users from 1.9 percentage points

[14] Figure A.4 in the Appendix presents an analogous plot at the weekly frequency using the main sample (October 2019 through April 2020).

in the baseline specification in column (1) to 2.1 percentage points.

## 3.2 Heterogeneity in Partisan Republican Optimism

This section presents evidence on sources of heterogeneity in the divergence of sentiment between partisan Republicans and other StockTwits users: (i) optimism about stocks that recently lost value, (ii) optimism about the prospects of large firms, and (iii) pessimism about US-listed Chinese stocks. For these heterogeneity tests, we estimate a triple difference specification of the following form:

$$
\begin{aligned}
Bull_{s,j,t} = \eta_{s,j} &+ \beta_1 \mathbb{1}Covid_t + \beta_2(\mathbb{1}Covid_t \times \mathbb{1}PartisanR_j) + \beta_3 Interaction_{s,t} \\
&+ \beta_4(\mathbb{1}Covid_t \times Interact_{s,t}) + \beta_5(\mathbb{1}PartisanR_j \times Interact_{s,t}) \\
&+ \beta_6(\mathbb{1}Covid_t \times \mathbb{1}PartisanR_j \times Interact_{s,t}) + \varepsilon_{s,j,t}
\end{aligned} \tag{3}
$$

where the dependent variable $Bull_{s,j,t}$ (multiplied by 100 for ease of interpretation) is an indicator for whether user $j$ is bullish about stock $s$ on day $t$, and $\eta_{s,j}$ is a user-stock fixed effect to absorb cross-user heterogeneity in sentiment across each stock. $\mathbb{1}Covid_t$ is an indicator for the COVID-19 period (March and April).[15] $\mathbb{1}PartisanR_j$ is an indicator variable for whether an individual is classified as a partisan Republican, and $Interact_{s,t}$ is an interaction variable for: (i) an indicator for whether stock $s$ is a member of the S&P500 as of February 29, 2020, (ii) an indicator for whether stock $s$ is a US-listed Chinese stock, or (iii) each stock's return over the preceding month (returns from 21 trading days before t to the trading day preceding t, denoted $month\ return_{s,t-1}$). Our sample time period runs from March 2019 through April 2020, and for the interaction with monthly lagged stock returns we constrain the sample to S&P500 firms.

[15]Though our main specifications do not take a stance on the timing of the divergence of beliefs by estimating monthly coefficients, it is simpler to present the triple interaction evidence in a pre-post framework. We choose the end of February as the event date because the daily fixed effects diverge in early March in Figure 3.

### 3.2.1 Pessimism about China

Republicans were more likely than Democrats to blame China for the emerging crisis in the United States (Perrett, 2020): Republican commentators and politicians (including President Trump) often referred to the coronavirus as the "Chinese Virus" or the "Wuhan Virus" to underscore the fact that China was COVID-19's likely country of origin.[16]

Given the sharp political divide on China during the COVID-19 period, it is natural to evaluate whether Republican political views also shaped investor beliefs about Chinese firms. We construct an indicator for Chinese ADRs in our sample (e.g., Baidu, Alibaba), and estimate the triple difference specification in (3) using an indicator for whether stock $s$ is a Chinese ADR. If partisan Republicans are more pessimistic about Chinese stocks during COVID, we should observe a negative triple interaction coefficient.

Column (1) of Table 4 presents the estimates from this specification. Consistent with the hypothesis that partisanship shapes investor beliefs about Chinese stocks, we find that partisan Republicans are approximately 7 percentage points more pessimistic about Chinese firms during the COVID-19 period than other StockTwits investors. For context, the coefficient on $\mathbb{1}\ Covid_t \times \mathbb{1}\ Interaction_s$ indicates that other users are more pessimistic about Chinese firms, but their sentiment during the COVID-19 period falls only 1.3 percentage points. The triple interaction is also substantially larger than the baseline 2 percentage point optimism gap we observe in the difference-in-differences coefficient $\mathbb{1}\ Covid_t \times \mathbb{1}\ PartisanR_j$.[17]

[16] In support of this, in Appendix Figure A.2 we present the daily time series for Google Search volume for the term "Chinese Virus." The time series has two peaks – one around the time of the Wuhan lockdown (Jan 25th), likely reflecting curiosity about a then-unnamed virus. The second peak was around a series of tweets by President Trump that mentioned the term "Chinese Virus" (March 19th) – e.g., see Figure A.3. The second peak is arguably when China's role became politicized in the U.S., and is coincident with the largest partisan differences in beliefs about Chinese stocks (see Figure 5).

[17] A potential concern is that our partisan classification selects StockTwits users who have a greater expressed interest in China and are abnormally attuned to matters that affect Chinese stocks, which may contribute to the pessimism result we observe. To address this, we count the number of pre-2020 posts or likes that mention the terms "China," "Chinese" or "Trade War" for each user, and add an indicator for users interested in these topics interacted with the COVID dummy. As we report in appendix Table A.2 (columns (2) - (6)), controlling for users' intensity of interest in China or Trade War has little impact on our estimated partisan optimism gap.

In addition, to show when this negativity emerged, we estimate a version of equation (3) that replaces the $\mathbb{1}Covid_t$ indicator with a series of weekly fixed effects. Figure 5 plots the triple interaction coefficient estimates, and indicates no significant pre-trends from March 2019 through early February 2020 (we also show a monthly version of this interaction showing no pre-trends back to January 2018 in appendix Figure A.5). The weekly point estimates give some indication of pessimism by partisan Republicans in early February, as cases grew rapidly in China, but the triple difference estimate becomes even more negative in mid-March. The timing of Republican beliefs about Chinese stocks is instructive: they did not become more pessimistic about these stocks during the COVID-19 outbreak in China; instead, they became pessimistic about them in mid-March when new cases in China had fallen, but the crisis in the U.S. was deepening. This points to a political, rather than economic, model for their beliefs.

Returning to the potential concern that our classification of partisan Republican could simply proxy for optimism, in appendix table A.3 we also examine Pre-Covid Optimists' views on US-listed Chinese stocks. We find that they are differentially *optimistic* about US-listed Chinese stocks, unlike partisan Republicans, who are differentially *pessimistic* (column (4) versus column (3)). This further supports our conclusion that partisan Republican is not a stand-in for optimism.

#### 3.2.2 Optimism about Large Stocks

In column (2), we report estimates from the specification in equation (3) using an indicator for membership in the S&P500 as an interaction. These estimates show that partisan Republicans are substantially more optimistic about firms in the S&P500 during the pandemic. Specifically, we estimate that partisan Republicans are 5.2 percentage points more optimistic about S&P500 firms during the COVID-19 period (March and April, 2020), relative to other users on StockTwits.

Given COVID-19 was a massive, economy-wide shock, it is interesting to see Republicans' differential optimism concentrated in large-cap stocks. While there are plenty of small-cap and micro-cap firms with high idiosyncratic volatility that are discussed often on StockTwits (e.g., Aurora Cannabis or Virgin Galactic), these were not the stocks where political disagreement manifested during the pandemic. Instead, it appeared in stocks that best represented beliefs about the market in general, like large, bell-weather stocks in the S&P500.

Column (3) confirms this interpretation. At the end of 2019, we run a year-long market-model regression with daily returns and recover the the fraction of variation explained by the market (R-squared). We then estimate the triple difference specification in equation (3) with each stock's market model R-squared as the interaction term. The result is clear: Republican disagreement during the COVID-19 period is concentrated among stocks with the highest share of systematic variance. Stocks with high levels of idiosyncratic variance were not the playing field of partisan disagreement during the pandemic.

### 3.2.3 Optimism about Stocks that Lost Value

Finally, another possible manifestation of the partisan divergence of opinions during COVID-19 is that partisan Republicans expect a faster and more complete economic recovery than other users, so that they would be more optimistic about stocks that lost the most value. To evaluate this possibility, we estimate the triple difference specification in (3) using the stock return over the preceding month (from 21 trading days before $t$ to the trading day preceding $t$, denoted $month\ return_{s,t-1}$) as the interaction variable. If partisan Republicans are more optimistic about stocks that recently lost value, we would expect a negative triple difference coefficient.[18]

Table 4 presents the results from estimating this specification in column (3), restricting attention to S&P500 stocks where partisan differences in opinion are clearest. Consistent

[18] Unlike the China and S&P500 interactions the $month\ return_{s,t-1}$ variable is time-varying within firm. Thus, unlike the specifications in columns (1) and (2), the coefficients on $month\ return_{s,t-1}$ and $PartisanR_j \times month\ return_{s,t-1}$ are not absorbed by the user-stock fixed effects.

with partisan Republican belief in a faster and more complete recovery, we estimate that partisan Republicans are around 10.7 percentage points more optimistic about the worst performing firms during the COVID-19 period. [19] This optimism about firms that recently lost value runs counter to the usual relation between recent market returns and investor beliefs on StockTwits, which typically exhibit significant momentum (indicated by the positive and significant estimate on the baseline coefficient $month\ return_{s,t-1}$). More than leading partisan Republicans to reduce their typical proclivity toward momentum, the results in this table indicate that partisan Republicans' investor beliefs became contrarian with respect to recent market movements.[20]

# 4 Partisan Disagreement and Stock Turnover

In this section, we connect differences in partisan investor beliefs to daily stock turnover, which increased considerably during the pandemic. In Figure 6, we plot the daily percentiles (10th, 25th, 50th, 75th and 90th) of stock turnover from January 2019 through April 2020. Consistent with the timing of the onset of the COVID-19 crisis, daily stock turnover sharply increased around the beginning of March 2020 and remained high through the end of our sample. In addition to this increase in daily stock turnover, there is a similarly large increase in the cross-sectional spread in daily turnover across firms.

## 4.1 Measuring Partisan Disagreement

We next turn to relating partisan differences in political beliefs to trading at the stock-day level. For this analysis, we construct a difference of opinion measure between partisan Republicans and other users. Following the approach in Cookson and Niessner (2020) for

[19] The estimated coefficient for the triple interaction equals 13.7%, multiplied by the worst performing firm's loss of 78.3% (Halliburton - see Table A.6), which equals our reported magnitude of 10.7.

[20] Table A.6 reports the 10 worst-performing S&P500 stocks for the period from January 1st through the market bottom on March 23rd. These stocks are in the energy sector (Halliburton and Schlumberger), airlines (United Airlines and Boeing Inc), and major retail (Macy's and Kohl's).

the two group case, we measure partisan disagreement at the stock-day level as:

$$Partisan\ Disagree_{s,t} = \left| sent_{s,t}^{PartisanR} - sent_{s,t}^{others} \right| \tag{4}$$

where $sent_{s,t}^{PartisanR}$ is the average of bullish ($= 1$) and bearish ($= -1$) messages about a stock $s$ on date $t$ for partisan Republican users, and $sent_{s,t}^{others}$ is defined analogously for other StockTwits users. We restrict attention to stock-days for which there are messages of both types (partisan Republican and other), which is necessary to compute $PartisanDisagree_{s,t}$.

## 4.2 Stock Turnover in the Cross Section

For our analysis of stock turnover in the cross-section, we focus on a daily panel of stock information from March 2019 through April 2020. Table 5 presents summary information about this sample. We estimate the effect of partisan disagreement on daily stock turnover using the following specification:

$$\begin{aligned} AbnormalLogTurnover_{s,t} = {} & \beta_1 \mathbb{1}Covid_t + \beta_2 Overall\ Disagree_{s,t} \\ & + \beta_3(\mathbb{1}Covid_t \times Overall\ Disagree_{s,t}) + \beta_4 Partisan\ Disagree_{s,t} \\ & + \beta_5(\mathbb{1}Covid_t \times Partisan\ Disagree_{s,t}) + FE + \delta Controls_{s,t} + \varepsilon_{st} \end{aligned} \tag{5}$$

where the dependent variable $AbnormalLogTurnover_{s,t}$ is the abnormal log turnover for stock $s$ on day $t$.[21] $\mathbb{1}Covid_t$ is an indicator for the COVID-19 crisis period (equal to one in March and April, 2020). $OverallDisagree_{s,t}$ is the standard deviation of stamped sentiment messages (bullish $= 1$, bearish $= -1$) about stock $s$ on day $t$, and $PartisanDisagree_{s,t}$ is the average divergence in sentiment between partisan Republicans and other users as defined in equation (4). To aid interpretation, the disagreement measures are standardized to have

[21]Following prior research on disagreement and trading volume (e.g., Cookson and Niessner (2020)), $AbnormalLogTurnover_{s,t}$ is the difference between log turnover on day $t$ and the average log turnover from $t-140$ to $t-20$ trading days (6-month period, skipping the most recent month).

a mean of 0 and a standard deviation of 1.

Stock fixed effects (FE) are included in all regressions. We include day fixed effects in some specifications, and in the others we include the $\mathbb{1}Covid_t$ indicator to provide a reference for the difference in stock turnover during the COVID-19 period. Fixed effects for the number of user $impressions_{s,t}$ (i.e., the count of the number of users who post bullish or bearish sentiment about a stock $s$ on day $t$) are included in all but the first regression. $Controls_{s,t}$ is a vector of standard controls from the literature: recent volatility (last five days), recent abnormal returns (last five, and previous 25 trading days), and abnormal log turnover for day $t-1$. Standard errors are double clustered by stock and day to account for, respectively, serial and within-day correlation in the errors.

Table 6 presents the results from estimating equation (5). In column (1), we present a benchmark specification that quantifies the rise in stock turnover during the pandemic: we estimate that the COVID-19 period has 36% more abnormal stock turnover, after accounting for stock fixed effects, which is consistent with the univariate evidence in Figure 6. In column (2), we include *number of impression* fixed effects to absorb user activity at the stock-day level, accounting flexibly for differences in attention (news, press releases, etc.). Controlling for attention in this way reduces the estimated coefficient on $\mathbb{1}Covid_t$ by more than half, to 16%.

In column (3), we also include $Overall\ Disagree_{s,t}$ and $\mathbb{1}Covid_t \times Overall\ Disagree_{s,t}$. Consistent with the literature, we see that overall disagreement correlates strongly with stock turnover: a standard deviation increase in disagreement is associated with 5% greater abnormal turnover outside of the COVID-19 period. However, during the pandemic, the relation between disagreement and turnover more than doubles in magnitude, increasing by almost 9 percentage points.

In column (4), we add $Partisan\ Disagree_{s,t}$ and $\mathbb{1}Covid_t \times Partisan\ Disagree_{s,t}$ to the specification. Our estimates imply that there is no relation between partisan disagreement and trading volume before COVID ($est = -0.008$, $se = 0.009$). However, during the pandemic, a standard deviation increase in partisan disagreement is associated with 10% greater stock turnover, which is 28% of the baseline rise in stock turnover during the COVID-19 period (column (1)), and 50% of the effect of attention on turnover.[22] The estimated magnitude of the $\mathbb{1}Covid_t \times Partisan\ Disagree_{s,t}$ coefficient is greater than the baseline coefficient for overall disagreement (0.101 versus 0.058). Moreover, this increase in the sensitivity to partisan disagreement during COVID reduces the magnitude of the $\mathbb{1}Covid_t \times Overall\ Disagree_{s,t}$ coefficient, and renders it statistically insignificant.

The remaining columns show that these inferences about the relationship between partisan disagreement and the cross-section of stock turnover are not sensitive to including day fixed effects (column (5)), nor to adding control variables often employed in the literature (column (6)).

Our findings and empirical design draw a tight connection between partisan disagreement and abnormal stock turnover that is unlikely to be driven by other factors. Our main coefficient of interest is $\beta_5$ on the $\mathbb{1}Covid_t \times Partisan\ Disagree_{s,t}$ term, which compares the abnormal stock turnover of high partisan disagreement stocks to that of low partisan disagreement stocks, before versus during the COVID-19 period.[23] In this context, we observe a strong link between partisan disagreement and abnormal stock turnover *only* after the emergence of COVID-19. Further, our tests draw a comparison between stock-days after removing differences in financial attention (by including fixed effects for the number of user impressions). Thus, any potential omitted variable must be (i) orthogonal to the number of users who post opinions about a stock on a particular day, and (ii) uniquely emerge as a confounder during the COVID-19 period.[24]

In our final column we take advantage of two unique characteristics of the increase in

[22] From columns (1) and (2), the inclusion of number of impressions fixed effects reduces the magnitude of the estimate on $\mathbb{1}Covid_t$ by 20.2 percentage points. The estimated magnitude on the $\mathbb{1}Covid_t \times Partisan\ Disagree_{s,t}$ term is 10.1, which is 50% of this drop.

[23] Figure A.6 presents a leads and lags plot at the monthly frequency from a specification that replaces the $\mathbb{1}Covid_t$ indicator with monthly fixed effects. The plot shows parallel pre-trends, with a positive coefficient that emerges in February, March and April.

[24] Moreover, we address the reverse causality concern that trading today causes disagreement today by estimating a lagged disagreement specification in appendix Table A.5. The results are similar.

partisan disagreement during the pandemic: (i) it reflects additional disagreement among investors, and (ii) because it does not generate a trading motive (beyond increasing overall disagreement), it has no direct relationship with turnover. In a standard IV setting, point (i) constitutes the relevance condition and point (ii) constitutes the exclusion restriction. Thus, we use partisan disagreement to investigate the causal impact of disagreement on trading volume, removing standard confounders such as the arrival of news. To the extent that the disagreement literature is interested in the disagreement-turnover elasticity to measure the relative contribution of disagreement and liquidity motives in generating trading volume (e.g., Kandel and Pearson, 1995; Kruger, 2020), our setting provides a unique opportunity to estimate this parameter.

Specifically, we use partisan disagreement as an instrument for overall disagreement, and report the second stage instrumented coefficients in column (7) of Table 6.[25] The IV estimate is 0.23 during the COVID period (0.045 + 0.185), significantly greater than the OLS magnitude of 0.142 (0.053 + 0.089) in column (3). Thus, a standard deviation increase in disagreement leads to 23% greater abnormal stock turnover.[26] To estimate an elasticity we run a log-log IV regression in appendix Table A.4 and obtain an abnormal turnover to disagreement elasticity of 0.66, with a standard error of 0.086.[27]

Taken together, this table demonstrates that partisan differences in investment beliefs contribute to the sharp rise in trading that emerged during the COVID-19 period. Our findings suggest that partisanship not only shapes investment beliefs, but also influences the extent of trading in the broader market.

[25] The first stage regressions and the OLS analogue are reported in appendix Table A.4. The relevance condition is strongly satisfied.

[26] Our instrumented estimate pre-COVID-19 is 4.5%, consistent with OLS estimates in the literature (e.g., Cookson and Niessner, 2020). The interaction with the pandemic period indicator suggests a heightened sensitivity of turnover to disagreement.

[27] In fact we use an inverse-hyperbolic-sine transformation of the overall (and partisan) disagreement variables to account for zero-valued observations.

# 5 Conclusion

Our paper provides evidence of a partisan divide in investor beliefs that emerges during the COVID-19 pandemic. Using novel data from StockTwits, we find that partisan Republicans remain significantly more optimistic about equities than other investors, and that this pattern persists through April 2020. Consistent with the narrative that partisanship shapes investor beliefs, Republicans express a nuanced pattern of investment beliefs: they are more optimistic about stocks that recently lost value but more pessimistic about US-listed Chinese stocks. The partisan disagreement we document explains 28% of the abnormal trading volume during the COVID-19 period.

It should surprise no one that Democrats and Republicans disagree. Partisans predictably disagree about environmental policy, abortion, immigration and gun rights, among other wedge issues. By contrast, partisan disagreement about equities during the COVID-19 pandemic *is* surprising, particularly given how unhelpful partisan identity is for equity valuation. After all, disagreement about stocks during COVID should reflect disagreement about the virulence of the virus, its rate of spread, likely government response, its effectiveness, and related epidemiological issues.

The fact that we find a partisan divide in investor beliefs perhaps reflects the unprecedented heights of political polarization we have reached (Abramowitz and Saunders, 2008; Bishop, 2008; Gentzkow, Shapiro, and Taddy, 2019). Political identity has become increasingly relevant for choices we make (Gerber and Huber, 2009; Chen and Rohla, 2018; McCartney and Zhang, 2019) and beliefs we hold (Bartels, 2002; Gerber, Huber, and Washington, 2010). Our analysis begs several questions: Will the partisan divide that emerged during the COVID-19 pandemic continue to shape investor beliefs and market outcomes after the health crisis is over? Or, if partisan investor disagreement subsides, can we expect partisan disagreement to reemerge when investors face the uncertainty of the next crisis? We leave these questions for future research.

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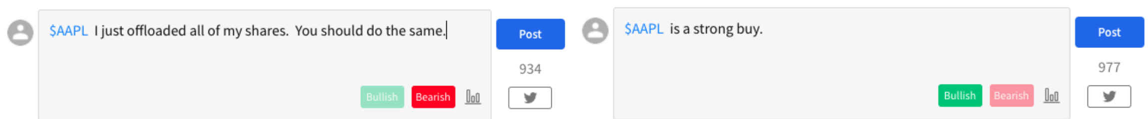
# Figures

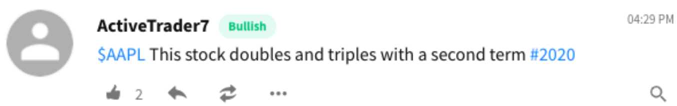
Figure 1: Examples of StockTwits Posts and Sentiment

This figure presents examples of StockTwits posts. Panel (a) presents two screenshots of the StockTwits posting interface – one with Bullish sentiment indicated, the other with Bearish sentiment. Panels (b) and (c) present two examples of posts about Apple (symbol $AAPL).

(a) Examples of StockTwits Interface for Bullish versus Bearish Posts




(b) Example Bullish Post




(c) Example Bearish Post

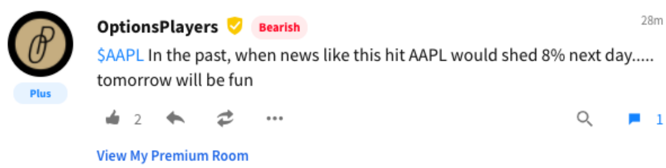
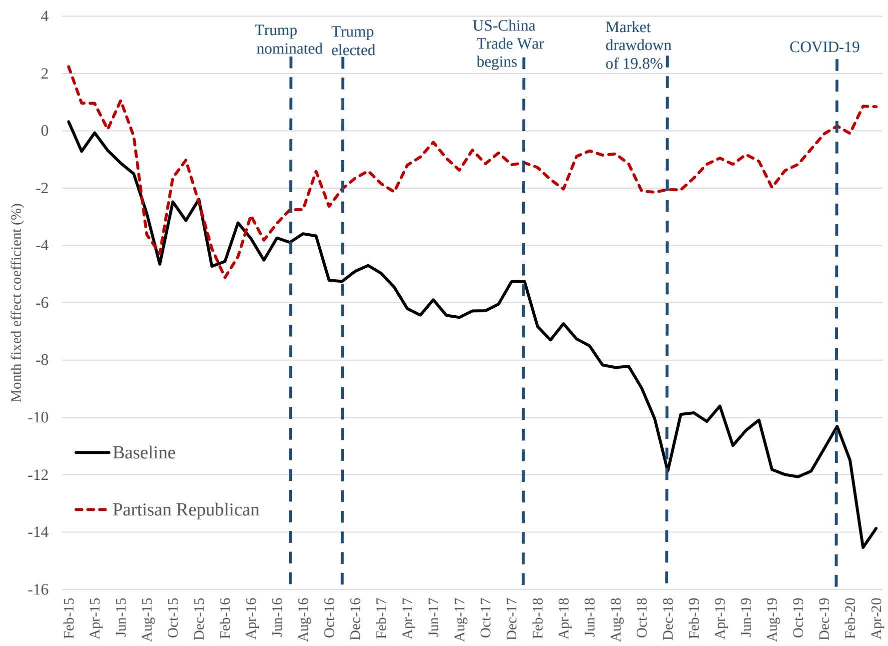


Figure 2: Optimism for Partisan Republicans versus Other Users (Jan 2015 – Apr 2020)

This plot shows how differences in optimism between partisan Republicans and other StockTwits users evolve over time from January 2015 to April 2020; the omitted (reference) period is January 2015. Panel (a) presents estimated monthly fixed effects – separately for Partisan Republicans and other users as a baseline – from a model with user-security fixed effects (following equation 1). Panel (b) presents monthly Google Search Intensity for the term "Trump stock market."

(a) Time Series of Monthly Fixed Effects




(b) Google Search Intensity for "Trump and Stock Market"

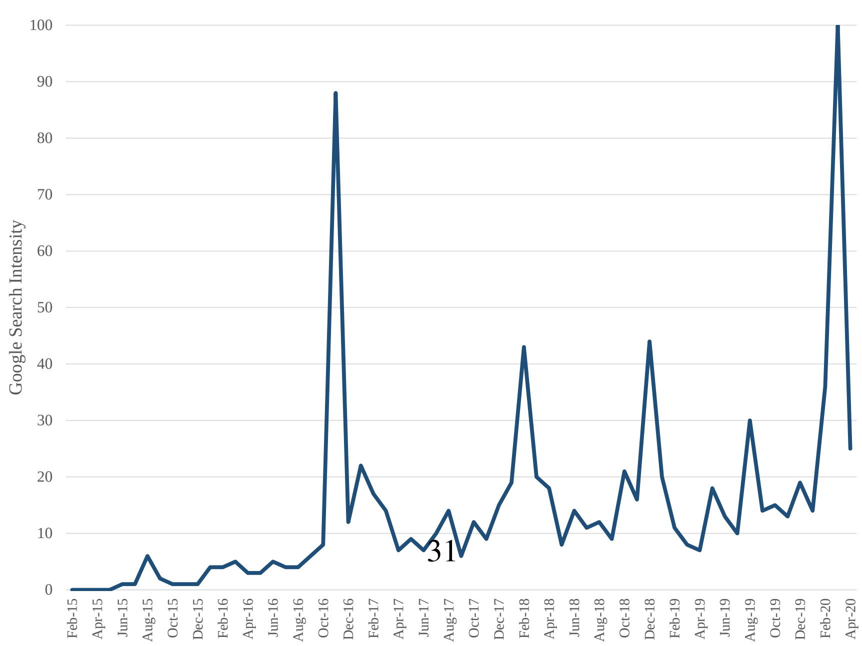
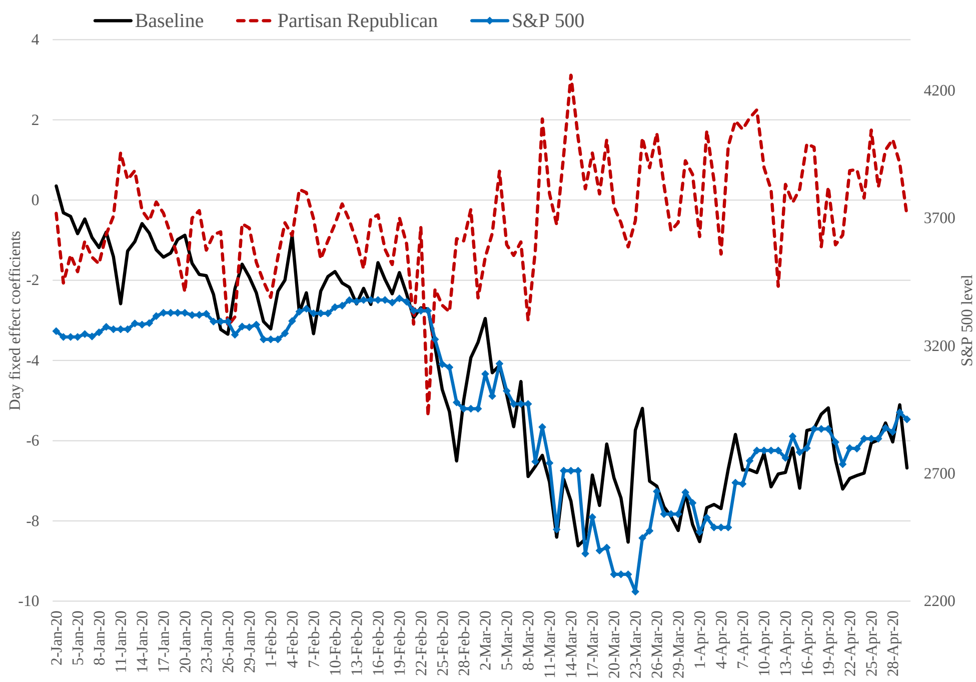


Figure 3: Optimism for Partisan Republicans versus Other Users Over Time – COVID Period

This plot shows how differences in optimism between partisan Republicans and other StockTwits users evolve over time from January 2020 until April 2020; the omitted (reference) period is January 1, 2020. Panel (a) presents the time series of daily fixed effects – separately for partisan Republicans and other users as a baseline – from a model with user-security fixed effects following equation 1. It also includes the level of the S&P 500 index on the right axis (fixing it at the level of the preceding trading day on non-trading days). Panel (b) presents the rolling one-week average of Google Search Intensity for “Trump and Stock Market” for the same period (January 2020 to April 2020).

(a) Time Series of Daily Fixed Effects (Jan 2020 – Apr 2020)




(b) Google Search Intensity for “Trump and Stock Market” (Jan 2020 – Apr 2020)

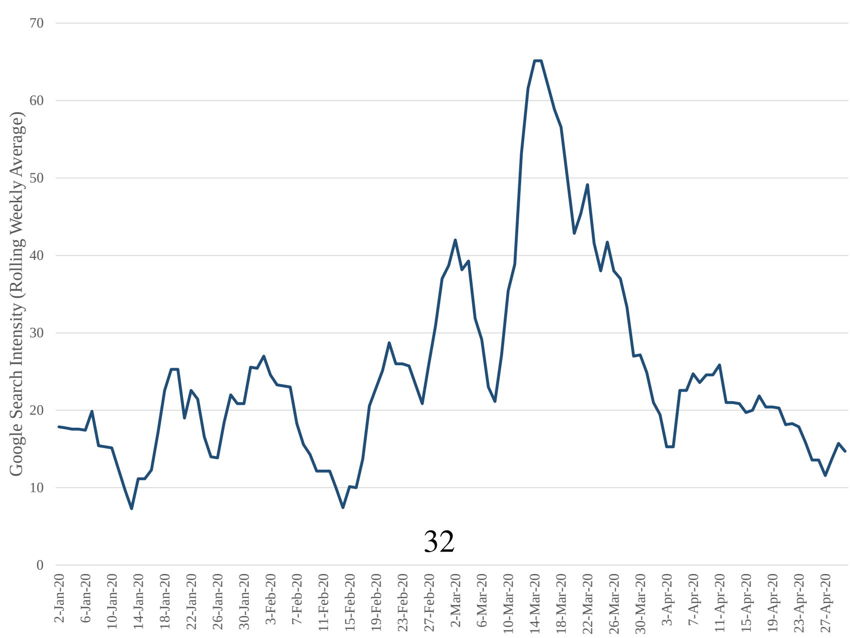
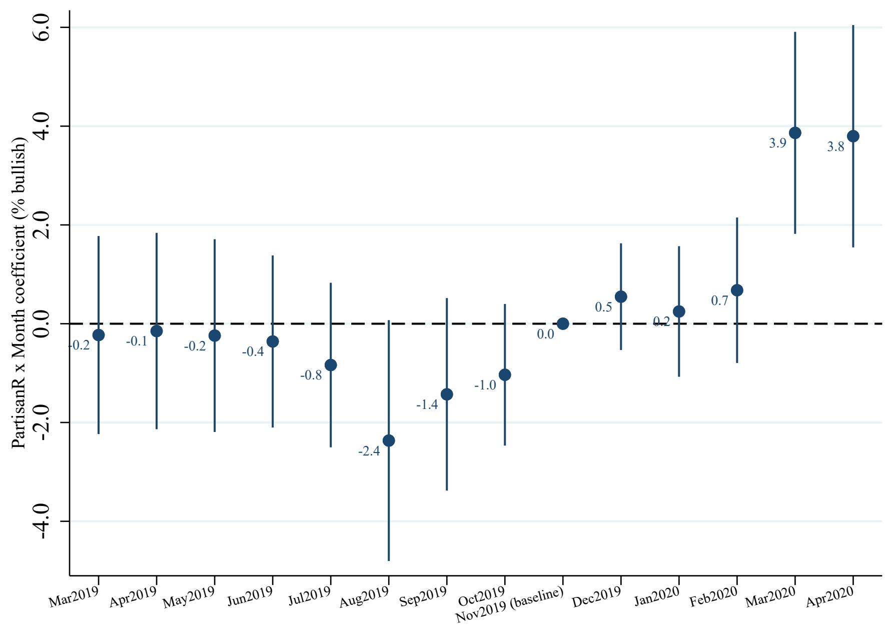


Figure 4: Partisan Republicans are More Optimistic than Other Users During COVID

This figure presents the timing of the emergence of Partisan Republican optimism during COVID. Each panel displays the estimated coefficients on the interaction between an indicator for whether a user is a Partisan Republican and monthly fixed effects from equation (2), which includes user-stock fixed effects. The sample follows Table 4 (March 2019 through April 2020). The vertical bars illustrate 95% confidence intervals with standard errors clustered by user. Panel (a) presents the estimated coefficients excluding small capitalization stocks below the 25th percentile of market equity as of December 31, 2019. Panel (b) presents the estimated coefficients drawn from the sample of S&P500 stocks.

(a) All Stocks, excluding Small Cap Stocks




(b) S&P500 Stocks

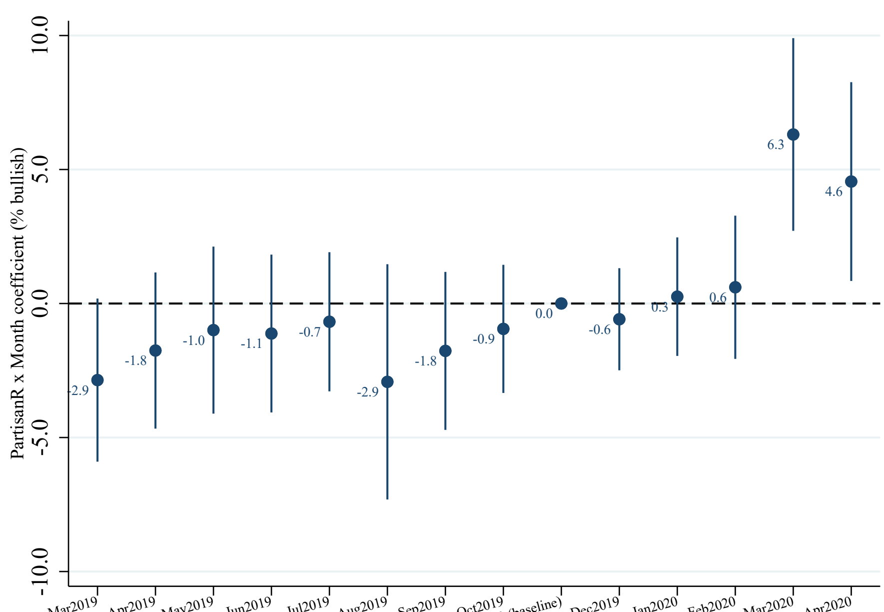


Figure 5: Partisan Republicans are Pessimistic about Chinese Stocks During COVID

This figure presents the time series of estimated coefficients on the triple interaction between an indicator for partisan Republican users, weekly fixed effects, and whether the stock is a U.S.-listed Chinese firm. These estimates are drawn from the weekly version of the specification in equation (3), which includes user-stock fixed effects. The sample follows Table 4 (March 2019 through April 2020). The vertical bars illustrate 95% confidence intervals with standard errors clustered by user.

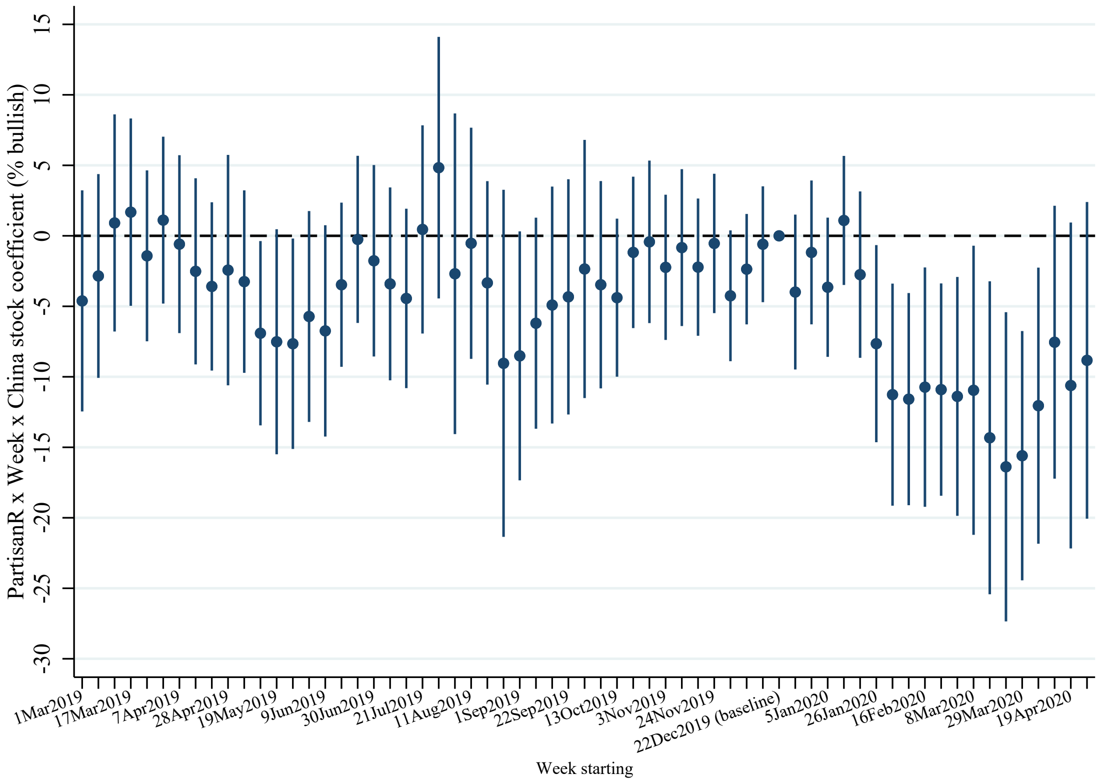
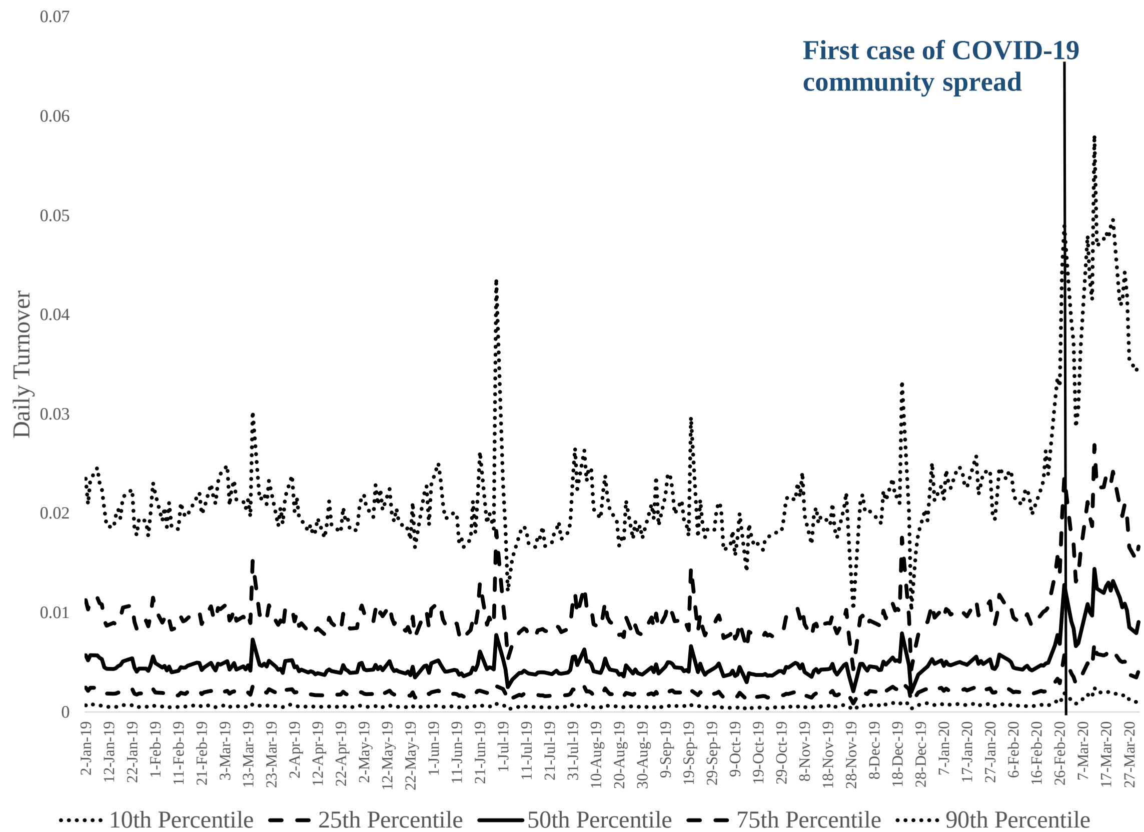


Figure 6: Percentiles of Daily Stock Turnover

This figure presents the time series of percentiles of daily stock turnover from January 2019 through the end of March 2020. Each line on the plot represents a time series plot of the daily turnover for the 10th, 25th, 50th, 75th, and 90th percentiles. The vertical line indicates the date of the first case of suspected local transmission of COVID-19 on February 26th, 2020.



## Tables

Table 1: Summary Statistics on StockTwits Data

This table presents summary statistics for the StockTwits data. Panel (a) presents counts of the various units of observations that comprise the data – users by partisan affiliation, securities, message sentiment and days.This provides an accounting of how we obtain the sample of user-security-day observations for our regression analysis. Panel (b) presents summary information on the observations used to classify messages and users as Republican, and number of messages posted by these users in the analysis sample.

(a) Dimensions of Data: Users, Securities, Sentiment and Days (Oct 2019 – Apr 2020)

| | Totals | Totals | |
|---|---|---|---|
| User-security-days (obs) | 2,282,605 | Days | 213 |
| Bullish | 1,848,059 | Pre-COVID | 152 |
| Bearish | 434,546 | COVID | 61 |
| | | | |
| Users | 119,434 | Securities | 1,042 |
| Republican | 3,448 | CRSP (e.g., Tesla) | 945 |
| Other users | 115,986 | Non-CRSP (e.g., Bitcoin) | 97 |

(b) Message and User Classification Details

| | |
|---|---|
| Messages considered (pre-2020) | 179,229,891 |
| Messages that contain partisan keywords | 70,031 |
| | |
| Users considered (pre-2020) | 780,908 |
| Users who made or liked *any* partisan message | 34,284 |
| Republican-identified users (i.e., R-D $\geq$ 4 messages + likes) | 6,191 |
| | |
| Republican presence in sample (October 2019-April 2020) | |
| Republican users | 3,448 |
| Republican observations (user-security-days) | 266,294 |

Table 2: Classification of Partisan Messages

This table presents contextual information regarding our classification of partisan Republican messages. Panel (a) presents the list of keywords used to flag partisan Republican tweets on StockTwits, which is the result of an iterative procedure that follows the language-based relative frequency approach of Gentzkow and Shapiro (2010). Panel (b) presents six example tweets that are flagged by this list of keywords – 3 Republican tweets and 3 Democrat tweets. In the iterative process that generates this keyword list, we seed the list of Republican keywords with “#MAGA” and “#Trump2020” and add terms to the list if they are used commonly by individuals who write posts containing these initial keywords. If these terms relate to the stock market (e.g., “S&P surging”) or are apolitical, we do not add them to the list. We repeat this iterative process to populate the partisan Republican keywords until we obtain a stable set of individuals identified as partisan Republican. We follow the same procedure to construct the list of Democrat keywords, starting instead with “Idiot Trump” and “Stupid Trump”. A StockTwits user is identified as a partisan Republican if they post or like at least four more Republican tweets than Democrat tweets.

(a) Partisan Keywords

| Republican keywords | | Democrat keywords | |
|---|---|---|---|
| "#MAGA" | "The Liberals" | "Drumpf" | "Orange Colored" |
| "Russia Hoax" | "Russian Collusion" | "Trump Nationalism" | "Idiot in Chief" |
| "#TRUMP2020" | "Stupid Dems" | "Trumptard" | "Criminal POTUS" |
| "Hussein Obama" | "Leftists" | "Trump is a liar" | "Trump is an idiot" |
| "Obummer" | "Trump Derangement" | "Idiot Trump" | "Clown Trump" |
| "Fake News Media" | "The Socialist" | "Faux News" | Imbecile Trump |
| "Crooked Hillary" | "MAGA 2020" | "Clown Child" | "Trump is an Imbecile" |
| "Snowflake" | "The Commie" | "Stupid Trump" | Orange Scum" |
| "Liberal Media" | "Libtard" | "Pig Clown" | "Scumpig Clown" |
| "Libs" | "Stupid Democrats" | "Liar in Chief" | "Lying Trump" |
| "Trump Hater" | "Sleepy Joe" | "Liar Trump" | "#IMPEACHTRUMP" |
| "Typical Liberal" | "Liberal Democrat" | "#F***TRUMP" | |
| "Liberal Agenda" | "You Liberal" | | |
| "Your Liberal" | | | |

(b) Examples of Partisan Tweets

| *Republican example messages* | |
|---|---|
| October 10, 2018 | "Fox News... This crash will teach those libtards!! $spy |
| October 27, 2019 | "Therapy bro, Trump derangement syndrome is no joke. Get some meds" |
| July 8, 2019 | "I probably won’t be alive to see it but the US is a short step to being a socialistic country. Only one election away. Vote TRUMP 2020 or else" |
| *Democrat example messages* | |
| January 29, 2018 | "$WYNN the only one less popular than Wynn now is the orange colored scumpig clown child masquerading as potus. BEARISH" |
| July 20, 2018 | $GM drumpf is killing this stock |
| November 2, 2018 | "Glad to see the Manipulator in Chief saw Apple earnings on Faux News scrambling for a deal now to try to save markets; very stable genius! |

Table 3: Are Partisan Republicans More Optimistic through the COVID-19 Crisis?

This table examines whether partisan Republicans exhibit greater optimism than other users through the COVID-19 crisis. The dependent variable is an indicator (multiplied by 100 to aid interpretation as a percentage) that a user $j$ declares as bullish about stock $s$ on day $t$. The specification (following equation 2) includes monthly fixed effects, and their interactions with an indicator for whether a user is a partisan Republican. The monthly fixed effects show the time series of sentiment for baseline users, whereas the $PartisanR_j \times$ month interactions show the extent to which partisan Republicans are differentially optimistic in that month. Column (1) is estimated on the top 1,042 securities by message volume on StockTwits (which includes non-stocks such as Bitcoin), column (2) restricts attention to stocks, column (3) restricts attention to stocks above the 25th percentile of NYSE market capitalization as of December 31st, 2019, and column (4) includes only stocks in the S&P500 as of March 1, 2020. The sample is at the user - security - day level, and runs from October 2019 to April 2020. Standard errors clustered by user are reported in brackets; $^{*}$,$^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1%.

| | Dependent variable: $\mathbb{1}$ x100 if $\text{Bull}_{s,j,t}$ | | | |
|---|---|---|---|---|
| | (1) All securities | (2) Only stocks | (3) Mkt cap> NYSE p(25) | (4) Only S&P500 stocks |
| $\mathbb{1}$ Oct2019 | 0.2 | 0.5$^{***}$ | -0.3 | -1.3$^{**}$ |
| | [0.2] | [0.2] | [0.3] | [0.5] |
| $\mathbb{1}$ Nov2019 (baseline) | 0.0 | 0.0 | 0.0 | 0.0 |
| $\mathbb{1}$ Dec2019 | 0.3$^{***}$ | 0.2$^{*}$ | 0.3 | 0.5 |
| | [0.1] | [0.1] | [0.2] | [0.4] |
| $\mathbb{1}$ Jan2020 | 0.7$^{***}$ | 0.3$^{**}$ | 0.8$^{***}$ | 1.0$^{**}$ |
| | [0.2] | [0.2] | [0.3] | [0.5] |
| $\mathbb{1}$ Feb2020 | -0.6$^{***}$ | -1.0$^{***}$ | -0.9$^{***}$ | -1.8$^{***}$ |
| | [0.2] | [0.2] | [0.3] | [0.6] |
| $\mathbb{1}$ Mar2020 | -3.6$^{***}$ | -3.4$^{***}$ | -5.9$^{***}$ | -7.6$^{***}$ |
| | [0.3] | [0.3] | [0.5] | [0.9] |
| $\mathbb{1}$ Apr2020 | -3.6$^{***}$ | -3.8$^{***}$ | -5.8$^{***}$ | -6.4$^{***}$ |
| | [0.2] | [0.2] | [0.5] | [0.8] |
| $\mathbb{1}$ $\text{PartisanR}_\mathbf{j}$ x $\mathbb{1}$ Oct2019 | -0.9$^{*}$ | -0.9$^{**}$ | -1.2 | -1.6 |
| | [0.4] | [0.4] | [0.8] | [1.3] |
| $\mathbb{1}$ $\text{PartisanR}_\mathbf{j}$ x $\mathbb{1}$ Dec2019 | 0.4 | 0.5 | 0.7 | -0.7 |
| | [0.3] | [0.3] | [0.5] | [0.9] |
| $\mathbb{1}$ $\text{PartisanR}_\mathbf{j}$ x $\mathbb{1}$ Jan2020 | 0.7 | 0.6$^{*}$ | 0.4 | 0.2 |
| | [0.4] | [0.4] | [0.6] | [1.0] |
| $\mathbb{1}$ $\text{PartisanR}_\mathbf{j}$ x $\mathbb{1}$ Feb2020 | 0.5 | 0.6 | 0.6 | 0.3 |
| | [0.5] | [0.4] | [0.7] | [1.3] |
| $\mathbb{1}$ $\text{PartisanR}_\mathbf{j}$ x $\mathbb{1}$ Mar2020 | 1.6$^{**}$ | 2.0$^{***}$ | 3.8$^{***}$ | 5.4$^{***}$ |
| | [0.6] | [0.5] | [0.9] | [1.7] |
| $\mathbb{1}$ $\text{PartisanR}_\mathbf{j}$ x $\mathbb{1}$ Apr2020 | 2.1$^{***}$ | 2.7$^{***}$ | 4.0$^{***}$ | 4.1$^{**}$ |
| | [0.6] | [0.5] | [0.9] | [1.7] |
| # observations | 1,936,128 | 1,676,915 | 642,575 | 252,213 |
| # clusters (users) | 75,417 | 69,388 | 37,398 | 19,283 |
| $R^2$ | .75 | .77 | .76 | .74 |
| Uncond. mean of dependent var. | 81.5 | 84.9 | 76.1 | 73.2 |
| User-security FE | Yes | Yes | Yes | Yes |

## Table 4: Heterogeneity in Partisan Republican Optimism

This table reports estimates from triple difference specifications following equation (3). The dependent variable is an indicator (multiplied by 100 to aid interpretation as a percentage) that a user $j$ declares as bullish about stock $s$ on day $t$. The $\mathbb{1}Covid_t$ variable is an indicator equal to one in March and April 2020; the $\mathbb{1}PartisanR_j$ indicator is equal to one for partisan Republican users. The Interaction variable varies by column: column (1) examines whether partisan differences in sentiment are different for US-listed Chinese firms; column (2) examines whether they are different for large firms (S&P500 firms as of Feb 29, 2020). Column (3) replaces the interaction with a continuous variable, the $R^2$ from a market model run with daily returns over the whole of 2019, to examine whether differential sentiment was driven by stocks that reflected beliefs about the market in general. Finally, column (4) examines whether partisan differences in sentiment are different for stocks based on their returns over the preceding month (also a continuous interaction). The sample is at the user-stock-day level, runs from March 2019 to April 2020, and covers 930 stocks (the subset of securities that have CRSP permnos out of the top 1,042 StockTwits securities by messages since 2013). Column (4) is run on S&P500 firms in our sample (148 stocks). Standard errors clustered by user are reported in brackets; $^{**}$ and $^{***}$ indicate statistical significance at 5% and 1%.

| | Dependent variable: $\mathbb{1}$ x100 if $\mathbf{Bull_{s,j,t}}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Interaction: $\mathbb{1}$ if China stock | Interaction: $\mathbb{1}$ if S&P500 stock | Interaction: market model $R^2$ | Interaction: 1month returns (S&P500 stocks) |
| $\mathbb{1}$ in $\mathrm{Covid}_{\mathbf{t}}$ period | -3.5$^{***}$<br>[0.2] | -3.1$^{***}$<br>[0.2] | -2.3$^{***}$<br>[0.2] | -6.4$^{***}$<br>[0.6] |
| $\mathbb{1}$ $\mathrm{Covid}_{\mathbf{t}}$ x $\mathbb{1}$ $\mathrm{PartisanR}_{\mathbf{j}}$ | 2.0$^{***}$<br>[0.5] | 1.1$^{**}$<br>[0.4] | 0.5<br>[0.4] | 6.0$^{***}$<br>[1.5] |
| $\mathbb{1}$ $\mathrm{Covid}_{\mathbf{t}}$ x $\mathbb{1}$ $\mathrm{Interaction}_{\mathbf{s}}$ | -1.3$^{**}$<br>[0.6] | -3.5$^{***}$<br>[0.6] | | |
| $\mathbb{1}$ $\mathrm{Covid}_{\mathbf{t}}$ x $\mathbb{1}$ $\mathrm{PartisanR}_{\mathbf{j}}$ x $\mathbb{1}$ $\mathrm{Interaction}_{\mathbf{s}}$ | -6.7$^{**}$<br>[3.4] | 5.2$^{***}$<br>[1.4] | | |
| $\mathbb{1}$ $\mathrm{Covid}_{\mathbf{t}}$ x market model $\mathrm{R}_{\mathbf{s}}^2$ | | | -12.9$^{***}$<br>[1.4] | |
| $\mathbb{1}$ $\mathrm{Covid}_{\mathbf{t}}$ x $\mathbb{1}$ $\mathrm{PartisanR}_{\mathbf{j}}$ x market model $\mathrm{R}_{\mathbf{s}}^2$ | | | 14.1$^{***}$<br>[3.6] | |
| Month $\mathrm{return}_{\mathbf{s,t-1}}$ | | | | 5.5$^{***}$<br>[1.8] |
| $\mathbb{1}$ $\mathrm{Covid}_{\mathbf{t}}$ x month $\mathrm{return}_{\mathbf{s,t-1}}$ | | | | -4.3$^{**}$<br>[1.9] |
| $\mathbb{1}$ $\mathrm{PartisanR}_{\mathbf{j}}$ x month $\mathrm{return}_{\mathbf{s,t-1}}$ | | | | 8.3$^{*}$<br>[4.8] |
| $\mathbb{1}$ $\mathrm{Covid}_{\mathbf{t}}$ x $\mathbb{1}$ $\mathrm{PartisanR}_{\mathbf{j}}$ x month $\mathrm{return}_{\mathbf{s,t-1}}$ | | | | -13.7$^{***}$<br>[4.9] |
| # observations | 3,036,393 | 3,036,393 | 2,943,488 | 462,827 |
| # clusters (users) | 93,045 | 93,045 | 91,649 | 26,738 |
| $R^2$ | .75 | .75 | .75 | .70 |
| Uncond. mean of dependent var. | 84.1 | 84.1 | 84.0 | 73.2 |
| User-security FE | Yes | Yes | Yes | Yes |

Table 5: Summary Statistics for Stock-Day Panel

This table presents summary statistics on the daily panel of financial data and disagreement measures for the March 2019–April 2020 sample we use for the analysis of daily stock turnover reported in Table 6.

| | Mean | Median | SD | O. |
|---|---|---|---|---|
| Abnormal log turnover$_{\mathbf{s,t}}$ | 0.431 | 0.200 | 1.164 | 96,407 |
| Overall disagreement$_{\mathbf{s,t}}$ | 0.044 | 0.251 | 0.978 | 96,407 |
| Partisan disagreement$_{\mathbf{s,t}}$ | -0.022 | -0.407 | 0.957 | 96,407 |
| Standard deviation of abnormal returns$_{\mathbf{s,(t-5\ to\ t-1)}}$ | 0.050 | 0.031 | 0.085 | 96,407 |
| Cumulative abnormal returns$_{\mathbf{s,(t-5\ to\ t-1)}}$ | 0.007 | -0.006 | 0.211 | 96,407 |
| Cumulative abnormal returns$_{\mathbf{s,(t-30\ to\ t-6)}}$ | -0.007 | -0.036 | 0.417 | 96,407 |
| Number of impressions$_{\mathbf{s,t}}$ | 27.824 | 11.000 | 51.988 | 96,407 |

Table 6: Partisan Disagreement and Daily Stock Turnover

This table examines how our measure of partisan disagreement from StockTwits relates to daily abnormal log turnover.

$$AbnormalLogTurnover_{s,t} = \beta_1 \mathbb{1}Covid_t + \beta_2 OverallDisagree_{s,t} + \beta_3(\mathbb{1}Covid_t \times OverallDisagree_{s,t})$$
$$+\beta_4 PartisanDisagree_{s,t} + \beta_5(\mathbb{1}Covid_t \times PartisanDisagree_{s,t}) + FE + \delta Controls_{s,t} + \varepsilon_{s,t}$$

$AbnormalLogTurnover_{s,t}$ is the difference between log turnover on day $t$ and the average log turnover from $t-140$ to $t-20$ trading days (6-month period, skipping the most recent month) for stock $s$. The $\mathbb{1}Covid_t$ indicator equals one after February 2020. $OverallDisagree_{s,t}$ is the standard deviation of stamped messages with sentiment (bullish $= 1$, bearish $= -1$), while $PartisanDisagree_{s,t}$ is the average divergence in sentiment between partisan Republicans and other users, following equation (4). Both disagreement measures are normalized to have a mean of zero and a unit standard deviation. Stock (permno) Fixed effects (FE) are included in all regressions; number of impressions and day fixed effects are included in some. Number of $impressions_{s,t}$ is the number of users that tweet with sentiment about each stock each day. Controls include abnormal log turnover on day $t-1$; volatility, measured as the standard deviation of abnormal returns over days $t-5$ to $t-1$; and cumulative abnormal returns measured over days $t-30$ to $t-6$ and $t-5$ to $t-1$. Column (7) presents the second stage estimates from an instrumental variables specification that uses $PartisanDisagree_{s,t}$ as an instrument for $OverallDisagree_{s,t}$; first stage results are available in Table A.4. The sample is at the stock - day level, and runs from March 2019 to April 2020. Standard errors separately clustered by stock (permno) and day are reported in brackets; ** and *** indicate statistical significance at 5% and 1%.

| | Dependent variable: Abnormal log turnover$_{s,t}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) Only $\mathbb{1}$ Covid | (2) + #Impress. FE | (3) + Overall disagree. | (4) + Partisan disagree. | (5) + Day FE | (6) + Controls | (7) IV version of (3) |
| $\mathbb{1}$ in Covid$_t$ period | 0.361*** | 0.159*** | 0.143*** | 0.150*** | | | 0.131*** |
| | [0.048] | [0.047] | [0.046] | [0.045] | | | [0.046] |
| Overall disagreement$_{s,t}$ | | | 0.053*** | 0.058*** | 0.060*** | 0.029*** | 0.045*** |
| | | | [0.008] | [0.011] | [0.011] | [0.006] | [0.009] |
| $\mathbb{1}$ Covid$_t$ x Overall disagree.$_{s,t}$ | | | 0.089*** | 0.025 | 0.012 | -0.015 | 0.185*** |
| | | | [0.023] | [0.028] | [0.028] | [0.017] | [0.031] |
| Partisan disagreement$_{s,t}$ | | | | -0.008 | -0.009 | -0.008 | |
| | | | | [0.009] | [0.009] | [0.005] | |
| $\mathbb{1}$ Covid$_t$ x Partisan disagree.$_{s,t}$ | | | | 0.101*** | 0.092*** | 0.066*** | |
| | | | | [0.022] | [0.021] | [0.014] | |
| Volatility of abnormal ret.$_{s,(t-5 \text{ to } t-1)}$ | | | | | | 0.061 | |
| | | | | | | [0.087] | |
| Cum. abnormal ret.$_{s,(t-5 \text{ to } t-1)}$ | | | | | | -0.223*** | |
| | | | | | | [0.029] | |
| Cum. abnormal ret.$_{s,(t-30 \text{ to } t-6)}$ | | | | | | -0.085*** | |
| | | | | | | [0.026] | |
| Abnormal log turnover$_{s,t-1}$ | | | | | | 0.513*** | |
| | | | | | | [0.014] | |
| # observations | 102,627 | 96,436 | 96,436 | 96,436 | 96,436 | 96,407 | 96,436 |
| # clusters (stocks) | 891 | 888 | 888 | 888 | 888 | 888 | 888 |
| # clusters (days) | 295 | 295 | 295 | 295 | 295 | 295 | 295 |
| $R^2$ | .27 | .59 | .60 | .60 | .61 | .75 | |
| Uncond. mean of dependent var. | 0.400 | 0.432 | 0.432 | 0.432 | 0.432 | 0.431 | 0.432 |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # of impressions$_{s,t}$ FE | . | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | . | . | . | . | Yes | Yes | . |

Internet Appendix to:

# Does Partisanship Shape Investor Beliefs? Evidence from the COVID-19 Pandemic

**J. Anthony Cookson, Joseph E. Engelberg and William Mullins**

We extend the series of daily optimism fixed effects in the top panel of Figure 3 from January 2017 to June 2020, and make it available online at http://www.tonycookson.com/data-and-programs.

[1]

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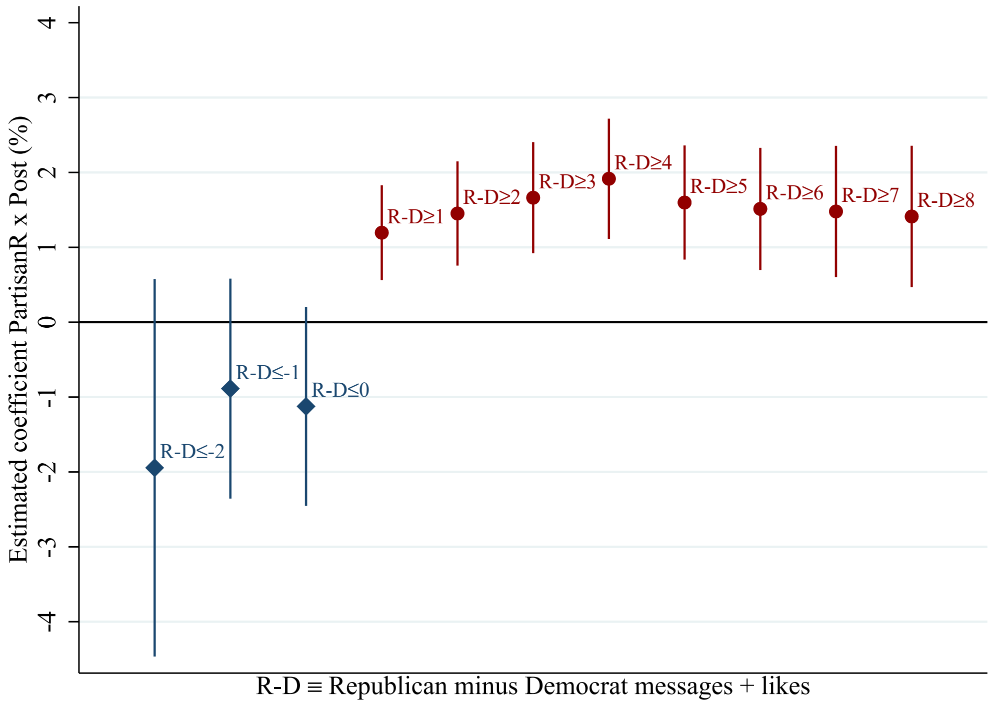
## Table A.1: Alternative measures of Partisanship

This table examines alternative measures of user partisanship. We define $R-D$ as a user's total number of pre-2020 Republican messages and likes, minus their Democrat messages and likes. Each column presents coefficients from the regression run in column (2) of Table 3 using different cutoffs for $R-D$ to define a partisan user. In the paper, we define a partisan Republican with $R-D \geq 4$ (column (7) in this table) i.e., users that have posted or liked at least four more Republican than Democratic messages pre-2020. $R-D$ values below zero correspond to likely partisan Democrats. The bottom row reports the number of partisan users defined by the various $R-D$ conditions. The dependent variable is an indicator (multiplied by 100) that a user $j$ declares as bullish about security $s$ on day $t$. The sample follows Table 3 (October 2019 through April 2020). $^{*}$,$^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1%.

| | Dependent variable: $\mathbb{1}$ x100 if $\text{Bull}_{\mathbf{s,j,t}}$ | | | | | R-D ≡ #Republican minus #Democrat messages & likes | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) R-D≤-2 | (2) R-D≤-1 | (3) R-D≤0 | (4) R-D≥1 | (5) R-D≥2 | (6) R-D≥3 | (7) R-D≥4 | (8) R-D≥5 | (9) R-D≥6 | (10) R-D≥7 | (11) R-D≥8 |
| Oct2019 | 0.2 | 0.2 | 0.3 | $0.5^{**}$ | $0.5^{***}$ | $0.4^{***}$ | $0.5^{***}$ | $0.4^{**}$ | $0.4^{**}$ | $0.3^{**}$ | $0.3^{**}$ |
| | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] |
| Nov2019 (baseline) | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Dec2019 | $0.3^{**}$ | $0.3^{***}$ | $0.3^{**}$ | 0.2 | 0.2 | 0.2 | $0.2^{*}$ | $0.3^{**}$ | $0.3^{**}$ | $0.2^{**}$ | $0.2^{**}$ |
| | [0.1] | [0.1] | [0.1] | [0.2] | [0.1] | [0.1] | [0.1] | [0.1] | [0.1] | [0.1] | [0.1] |
| Jan2020 | $0.5^{***}$ | $0.5^{***}$ | $0.5^{***}$ | 0.2 | $0.3^{*}$ | $0.3^{*}$ | $0.3^{**}$ | $0.4^{**}$ | $0.4^{***}$ | $0.4^{***}$ | $0.4^{***}$ |
| | [0.1] | [0.1] | [0.1] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] |
| Feb2020 | $-0.9^{***}$ | $-0.9^{***}$ | $-0.8^{***}$ | $-1.2^{***}$ | $-1.1^{***}$ | $-1.1^{***}$ | $-1.0^{***}$ | $-1.0^{***}$ | $-0.9^{***}$ | $-1.0^{***}$ | $-0.9^{***}$ |
| | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] |
| Mar2020 | $-3.1^{***}$ | $-3.0^{***}$ | $-3.0^{***}$ | $-3.7^{***}$ | $-3.5^{***}$ | $-3.5^{***}$ | $-3.4^{***}$ | $-3.3^{***}$ | $-3.3^{***}$ | $-3.3^{***}$ | $-3.2^{***}$ |
| | [0.2] | [0.2] | [0.3] | [0.3] | [0.3] | [0.3] | [0.3] | [0.3] | [0.3] | [0.3] | [0.3] |
| Apr2020 | $-3.3^{***}$ | $-3.3^{***}$ | $-3.3^{***}$ | $-4.2^{***}$ | $-4.0^{***}$ | $-3.9^{***}$ | $-3.8^{***}$ | $-3.6^{***}$ | $-3.6^{***}$ | $-3.6^{***}$ | $-3.5^{***}$ |
| | [0.2] | [0.2] | [0.2] | [0.3] | [0.3] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] |
| $\mathbb{1}$ $\text{PartisanR}_{\mathbf{j}}$ x Oct2019 | 1.1 | 0.8 | 0.1 | -0.5 | $-0.6^{*}$ | $-0.7^{*}$ | $-0.9^{**}$ | -0.6 | -0.5 | -0.5 | -0.5 |
| | [0.9] | [0.7] | [0.6] | [0.3] | [0.3] | [0.4] | [0.4] | [0.4] | [0.4] | [0.5] | [0.5] |
| $\mathbb{1}$ $\text{PartisanR}_{\mathbf{j}}$ x Dec2019 | 0.7 | -0.1 | 0.1 | 0.3 | 0.4 | 0.4 | 0.5 | 0.3 | 0.4 | 0.6 | 0.6 |
| | [0.9] | [0.6] | [0.5] | [0.2] | [0.3] | [0.3] | [0.3] | [0.3] | [0.4] | [0.4] | [0.4] |
| $\mathbb{1}$ $\text{PartisanR}_{\mathbf{j}}$ x Jan2020 | -0.3 | -0.7 | -0.8 | $0.5^{*}$ | $0.6^{*}$ | $0.7^{*}$ | $0.6^{*}$ | 0.4 | 0.5 | 0.7 | 0.7 |
| | [1.3] | [0.8] | [0.6] | [0.3] | [0.3] | [0.3] | [0.4] | [0.4] | [0.4] | [0.4] | [0.5] |
| $\mathbb{1}$ $\text{PartisanR}_{\mathbf{j}}$ x Feb2020 | -0.0 | -0.8 | -0.8 | $0.6^{*}$ | 0.6 | $0.7^{*}$ | 0.6 | 0.1 | 0.2 | 0.3 | 0.1 |
| | [1.3] | [0.9] | [0.7] | [0.4] | [0.4] | [0.4] | [0.4] | [0.5] | [0.5] | [0.5] | [0.6] |
| $\mathbb{1}$ $\text{PartisanR}_{\mathbf{j}}$ x Mar2020 | -1.1 | -1.3 | $-1.8^{**}$ | $1.3^{***}$ | $1.5^{***}$ | $1.7^{***}$ | $2.0^{***}$ | $1.7^{***}$ | $1.6^{***}$ | $1.8^{***}$ | $1.7^{**}$ |
| | [1.1] | [0.9] | [0.9] | [0.5] | [0.5] | [0.5] | [0.5] | [0.5] | [0.6] | [0.6] | [0.7] |
| $\mathbb{1}$ $\text{PartisanR}_{\mathbf{j}}$ x Apr2020 | -2.2 | -0.8 | -0.9 | $2.2^{***}$ | $2.4^{***}$ | $2.7^{***}$ | $2.7^{***}$ | $2.1^{***}$ | $2.0^{***}$ | $2.0^{***}$ | $1.9^{***}$ |
| | [1.8] | [1.1] | [0.9] | [0.4] | [0.5] | [0.5] | [0.5] | [0.5] | [0.5] | [0.6] | [0.6] |
| # observations | 1,676,915 | 1,676,915 | 1,676,915 | 1,676,915 | 1,676,915 | 1,676,915 | 1,676,915 | 1,676,915 | 1,676,915 | 1,676,915 | 1,676,915 |
| # clusters (users) | 69,388 | 69,388 | 69,388 | 69,388 | 69,388 | 69,388 | 69,388 | 69,388 | 69,388 | 69,388 | 69,388 |
| $R^2$ | 0.77 | 0.77 | 0.77 | 0.77 | 0.77 | 0.77 | 0.77 | 0.77 | 0.77 | 0.77 | 0.77 |
| Uncond. mean of dep. var. | 84.9 | 84.9 | 84.9 | 84.9 | 84.9 | 84.9 | 84.9 | 84.9 | 84.9 | 84.9 | 84.9 |
| User-Security FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # users meeting R-D condition | 323 | 1,085 | 1,448 | 10,048 | 5,426 | 3,689 | 2,754 | 2,238 | 1,873 | 1,569 | 1,344 |

Figure A.1: Plotting coefficients from Table A.1

The figure below plots the coefficients for the $PartisanR_j \times Post_t$ coefficients from Table A.1 using alternative thresholds for the intensity and direction of the partisanship classification. The regression specification in Table A.1 considers a single post period, rather than estimating separate March and April 2020 coefficients, to simplify exposition. The first three coefficients (corresponding to $R-D$ values of $\leq$-2, -1, and 0), are likely Democratic partisans (blue diamonds). $R-D$ values of $\geq$1 and higher are likely Republican partisans (red circles). For example, a user with $R-D \geq 5$ has at least five more Republican than Democrat pre-2020 likes and/or posted messages.



## Table A.2: Are partisan Republicans just optimistic? Or interested in the China Trade War?

This table examines whether the $\mathbb{1}PartisanR_j$ user variable reflects users who post frequently about the U.S.-China Trade War, users that post often about China, or "Pre-Covid Optimists" (i.e., users *always* declaring bullish sentiment pre-2020). Each column presents coefficients from the baseline regression run in column (2) of Table 3, but combines all time periods into an (omitted) pre-period and a Post indicator ($\mathbb{1}Covid_t$) equal to one after February 2020, to simplify exposition. Column (1) reports the baseline estimates for comparison. Columns (2)-(3) add an interaction of $Covid_t$ with an indicator for a user being in the top quartile or decile of Trade War-related posts and likes pre-2020. Columns (4)-(6) focus on pre-2020 China-related posts and likes. Column (7) instead adds an interaction with Pre-Covid Optimists. The dependent variable is an indicator (multiplied by 100) that a user $j$ declares as bullish about security $s$ on day $t$. The sample follows Table 4 (March 2019 through April 2020). $^{*}$,$^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1%.

| | Dependent variable: $\mathbb{1}$ x100 if $\mathrm{Bull}_{s,j,t}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1)<br>Baseline | (2)<br>$\mathrm{Interact}_j$: TradeWar mentions $\geq$ p75 | (3)<br>$\mathrm{Interact}_j$: TradeWar mentions $\geq$ p90 | (4)<br>$\mathrm{Interact}_j$: China mentions $\geq$ p50 | (5)<br>$\mathrm{Interact}_j$: China mentions $\geq$ p75 | (6)<br>$\mathrm{Interact}_j$: China mentions $\geq$ p90 | (7)<br>$\mathrm{Interact}_j$: Pre-Covid Optimists |
| $\mathbb{1}$ in $\mathrm{Covid}_t$ period | -3.6$^{***}$ | -3.4$^{***}$ | -3.6$^{***}$ | -3.7$^{***}$ | -3.6$^{***}$ | -3.7$^{***}$ | -4.1$^{***}$ |
| | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] | [0.2] |
| $\mathbb{1}$ $\mathrm{Covid}_t$ x $\mathbb{1}$ $\mathrm{PartisanR}_j$ | 1.9$^{***}$ | 2.2$^{***}$ | 1.9$^{***}$ | 1.8$^{***}$ | 1.9$^{***}$ | 1.7$^{***}$ | 2.1$^{***}$ |
| | [0.5] | [0.5] | [0.5] | [0.6] | [0.6] | [0.5] | [0.5] |
| $\mathbb{1}$ $\mathrm{Covid}_t$ x $\mathbb{1}$ $\mathrm{Interaction}_j$ | | -0.6 | 0.1 | 0.3 | -0.1 | 0.8 | 1.8$^{***}$ |
| | | [0.4] | [0.7] | [0.4] | [0.5] | [0.7] | [0.3] |
| # observations | 3,036,393 | 3,036,393 | 3,036,393 | 3,036,393 | 3,036,393 | 3,036,393 | 3,036,393 |
| # clusters (users) | 93,045 | 93,045 | 93,045 | 93,045 | 93,045 | 93,045 | 93,045 |
| $R^2$ | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 | 0.75 |
| Uncond. mean of dependent var. | 84.1 | 84.1 | 84.1 | 84.1 | 84.1 | 84.1 | 84.1 |
| User-Security FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

## Table A.3: Pre-Covid optimists are bullish about Chinese stocks, but Partisan Republicans are Bearish

This table examines whether Pre-Covid Optimists (i.e., users *always* declaring bullish sentiment before 2020) are differentially bullish about U.S.-listed Chinese stocks during the pandemic. Each column presents coefficients from the baseline regression run in column (2) of Table 3, but combines all time periods into an (omitted) pre-period and a Post indicator ($\mathbb{1}Covid_t$) equal to one after February2020, to simplify exposition. Column (1) provides a baseline for $\mathbb{1}PartisanR_j$,while Column (3) shows a baseline for $Pre-CovidOptimists_j$. For reference, column (3) shows that Partisan Republicans are differentially *pessimistic* about U.S.-listed Chinese stocks (as shown in Table 4). Column (4) examines whether $Pre-CovidOptimists_j$ are differentially bullish about Chinese stocks. The dependent variable is an indicator (multiplied by 100) that a user $j$ declares as bullish about security $s$ on day $t$. The sample follows Table 4 (March 2019 through April 2020). $^{*}$,$^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1%.

| | Dependent variable: $\mathbb{1}$ x100 if $\text{Bull}_{s,j,t}$ | | | |
|---|---|---|---|---|
| | (1) Baseline for Partisans | (2) Baseline for Pre-Covid Optimists | (3) Adding China stock interaction to (1) | (4) Adding China stock interaction to (2) |
| $\mathbb{1}$ in $\text{Covid}_t$ period | -3.6$^{***}$ | -3.7$^{***}$ | -3.5$^{***}$ | -3.6$^{***}$ |
| | [0.2] | [0.2] | [0.2] | [0.2] |
| $\mathbb{1}$ $\text{Covid}_t$ x $\mathbb{1}$ $\text{PartisanR}_j$ | 1.9$^{***}$ | | 2.1$^{***}$ | |
| | [0.5] | | [0.5] | |
| $\mathbb{1}$ $\text{Covid}_t$ x $\mathbb{1}$ Pre-Covid $\text{Optimists}_j$ | | 1.7$^{***}$ | | 1.6$^{***}$ |
| | | [0.3] | | [0.3] |
| $\mathbb{1}$ $\text{Covid}_t$ x $\mathbb{1}$ China $\text{stock}_s$ | | | -1.3$^{**}$ | -2.5$^{***}$ |
| | | | [0.6] | [0.8] |
| $\mathbb{1}$ $\text{Covid}_t$ x $\mathbb{1}$ $\text{PartisanR}_j$ x $\mathbb{1}$ China $\text{stock}_s$ | | | -6.7$^{**}$ | |
| | | | [3.4] | |
| $\mathbb{1}$ $\text{Covid}_t$ x $\mathbb{1}$ Pre-Covid $\text{Optimists}_j$ x $\mathbb{1}$ China $\text{stock}_s$ | | | | 3.1$^{***}$ |
| | | | | [1.0] |
| # observations | 3,036,393 | 3,036,393 | 3,036,393 | 3,036,393 |
| # clusters (users) | 93,045 | 93,045 | 93,045 | 93,045 |
| $R^2$ | 0.75 | 0.75 | 0.75 | 0.75 |
| Uncond. mean of dependent var. | 84.1 | 84.1 | 84.1 | 84.1 |
| User-Security FE | Yes | Yes | Yes | Yes |

Table A.4: Instrumental Variable estimates of the sensitivity of Turnover to Disagreement

This table provides the first stage estimates for column (7) in Table 6, which uses $PartisanDisagree_{s,t}$ as an instrument for $OverallDisagree_{s,t}$ (and similarly for the interaction with $Covid_t$). Column (2) reports the instrumented coefficients found in Table 6, while column (1) reports the OLS equivalents. Columns (4) and (5) report the first stage regressions: the Sanderson-Windmeijer (2015) multivariate F-test statistics are 5,332 and 2,288 respectively, indicating a strong first stage. Column (3) is a variant of (2) where we replace $OverallDisagreement_{s,t}$ with its inverse hyperbolic sine (IHS), and similarly for the instrument, so as to estimate the elasticity of abnormal turnover to disagreement. Our estimate is 0.66, calculated as $= \hat{\beta} \frac{1}{\sqrt{\bar{x}^2+1}} \frac{\bar{x}}{\bar{y}}$, where $\bar{y}$ and $\bar{x}$ are the sample means of the dep. variable and $OverallDisagree_{s,t}$ , and $\hat{\beta}$ is the sum of both $OverallDisagree_{s,t}$ coefficients). The sample and variable definitions follow Table 6. $AbnormalLogTurnover_{s,t}$ is the difference between log turnover on day $t$ and the average log turnover from $t-140$ to $t-20$ trading days (6-month period, skipping most recent month) for stock $s$. The $Covid_t$ indicator equals one after February 2020. $OverallDisagree_{s,t}$ is the standard deviation of stamped messages with sentiment (bullish $=1$, bearish $=-1$), while $PartisanDisagree_{s,t}$ is the average divergence in sentiment between partisan Republicans and other users, following equation (4). Both disagreement measures are normalized to have a mean of zero and a unit standard deviation (except in column (3)). Fixed effects (FE) for stock (permno) and number of $impressions_{s,t}$ are included in all regressions. Number of $impressions_{s,t}$ is the number of users that tweet with sentiment about each stock each day. Standard errors separately clustered by stock (permno) and day are reported in brackets; $^{*}$,$^{**}$ and $^{***}$ indicate statistical significance at 10%, 5% and 1%.

| | Dep. var.: Abnormal log turnover$_{s,t}$ | | | Dep. var.: Overall dis.$_{s,t}$ | Dep. var.: $\mathbb{1}$ Covid$_t$ x Overall dis.$_{s,t}$ |
|---|---|---|---|---|---|
| | (1) OLS | (2) IV | (3) IV (elasticity) | (4) IV first stage | (5) IV first stage |
| $\mathbb{1}$ in Covid$_t$ period | 0.143$^{***}$ | 0.131$^{***}$ | -0.095 | 0.004 | 0.118$^{***}$ |
| | [0.046] | [0.046] | [0.071] | [0.019] | [0.026] |
| Overall disagreement$_{s,t}$ | 0.053$^{***}$ | 0.045$^{***}$ | | | |
| | [0.008] | [0.009] | | | |
| $\mathbb{1}$ Covid$_t$ x Overall disagreement$_{s,t}$ | 0.089$^{***}$ | 0.185$^{***}$ | | | |
| | [0.023] | [0.031] | | | |
| IHS(Overall disagreement$_{s,t}$) | | | 0.128$^{***}$ | | |
| | | | [0.024] | | |
| $\mathbb{1}$ Covid$_t$ x IHS(Overall disagreement$_{s,t}$) | | | 0.519$^{***}$ | | |
| | | | [0.087] | | |
| Partisan disagreement$_{s,t}$ | | | | 0.694$^{***}$ | 0.002 |
| | | | | [0.009] | [0.001] |
| $\mathbb{1}$ Covid$_t$ x Partisan disagreement$_{s,t}$ | | | | -0.045$^{***}$ | 0.626$^{***}$ |
| | | | | [0.013] | [0.018] |
| # observations | 96,436 | 96,436 | 96,436 | 96,436 | 96,436 |
| # clusters (stocks) | 888 | 888 | 888 | 888 | 888 |
| # clusters (days) | 295 | 295 | 295 | 295 | 295 |
| $R^2$ | 0.60 | | | 0.52 | 0.42 |
| Uncond. mean of dependent var. | 0.432 | 0.432 | 0.432 | 0.044 | 0.019 |
| Stock FE | Yes | Yes | Yes | Yes | Yes |
| # of impressions$_{s,t}$ FE | Yes | Yes | Yes | Yes | Yes |
| Elasticity estimate | | | 0.663 | | |
| Elasticity s.e. | | | 0.086 | | |

## Table A.5: Robustness test: using lagged disagreement measures in Turnover regressions

This table is a variant of Table 6 in which we replace both $OverallDisagree_{s,t}$ and $PartisanDisagree_{s,t}$ with their one-trading-day lags. There are no other differences in specification. Using lagged disagreement requires sentiment messages on day $t-1$ and impression fixed effects require them on day $t$: this joint requirement shrinks our sample relative to Table 6. $^{**}$ and $^{***}$ indicate statistical significance at 5% and 1%.

| | Dependent variable: Abnormal log turnover$_{s,t}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) Only 𝟙 Covid | (2) + #Impress. FE | (3) + Overall disagree. | (4) + Partisan disagree. | (5) + Day FE | (6) + Controls | (7) IV version of (3) |
| 𝟙 in Covid$_t$ period | 0.361$^{***}$ | 0.159$^{***}$ | 0.084 | 0.092$^{*}$ | | | 0.072 |
| | [0.048] | [0.047] | [0.054] | [0.053] | | | [0.054] |
| Overall disagreement$_{s,t-1}$ | | | 0.061$^{***}$ | 0.078$^{***}$ | 0.081$^{***}$ | -0.060$^{***}$ | 0.035$^{***}$ |
| | | | [0.009] | [0.011] | [0.011] | [0.006] | [0.011] |
| 𝟙 Covid$_t$ x Overall disagree.$_{s,t-1}$ | | | 0.148$^{***}$ | 0.102$^{***}$ | 0.084$^{**}$ | 0.038$^{**}$ | 0.235$^{***}$ |
| | | | [0.031] | [0.034] | [0.034] | [0.018] | [0.041] |
| Partisan disagreement$_{s,t-1}$ | | | | -0.027$^{***}$ | -0.026$^{***}$ | 0.074$^{***}$ | |
| | | | | [0.008] | [0.008] | [0.006] | |
| 𝟙 Covid$_t$ x Partisan disagree.$_{s,t-1}$ | | | | 0.081$^{***}$ | 0.073$^{***}$ | 0.033$^{**}$ | |
| | | | | [0.025] | [0.024] | [0.014] | |
| Volatility of abnormal ret.$_{s,(t-5\ to\ t-1)}$ | | | | | | 0.209$^{***}$ | |
| | | | | | | [0.077] | |
| Cum. abnormal ret.$_{s,(t-5\ to\ t-1)}$ | | | | | | -0.209$^{***}$ | |
| | | | | | | [0.026] | |
| Cum. abnormal ret.$_{s,(t-30\ to\ t-6)}$ | | | | | | -0.063$^{**}$ | |
| | | | | | | [0.025] | |
| Abnormal log turnover$_{s,t-1}$ | | | | | | 0.569$^{***}$ | |
| | | | | | | [0.013] | |
| # observations | 102,627 | 96,436 | 70,842 | 70,842 | 70,842 | 70,817 | 70,842 |
| # clusters (stocks) | 891 | 888 | 838 | 838 | 838 | 838 | 838 |
| # clusters (days) | 295 | 295 | 295 | 295 | 295 | 295 | 295 |
| $R^2$ | 0.27 | 0.59 | 0.63 | 0.63 | 0.64 | 0.80 | |
| Uncond. mean of dependent var. | 0.400 | 0.432 | 0.461 | 0.461 | 0.461 | 0.461 | 0.461 |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # of impressions$_{s,t}$ FE | . | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | . | . | . | . | Yes | Yes | . |

Figure A.2: Google Search Intensity for "Chinese Virus"

This figure presents the daily time series of Google Search Intensity for the term "Chinese Virus" from December 25, 2019 through April 30, 2020. The indicated peak is March 19th, which takes place after a series of tweets by President Trump mentioning the term, "Chinese Virus." The initial peak occurs on January 25, 2020, two days after Wuhan instituted its lockdown.

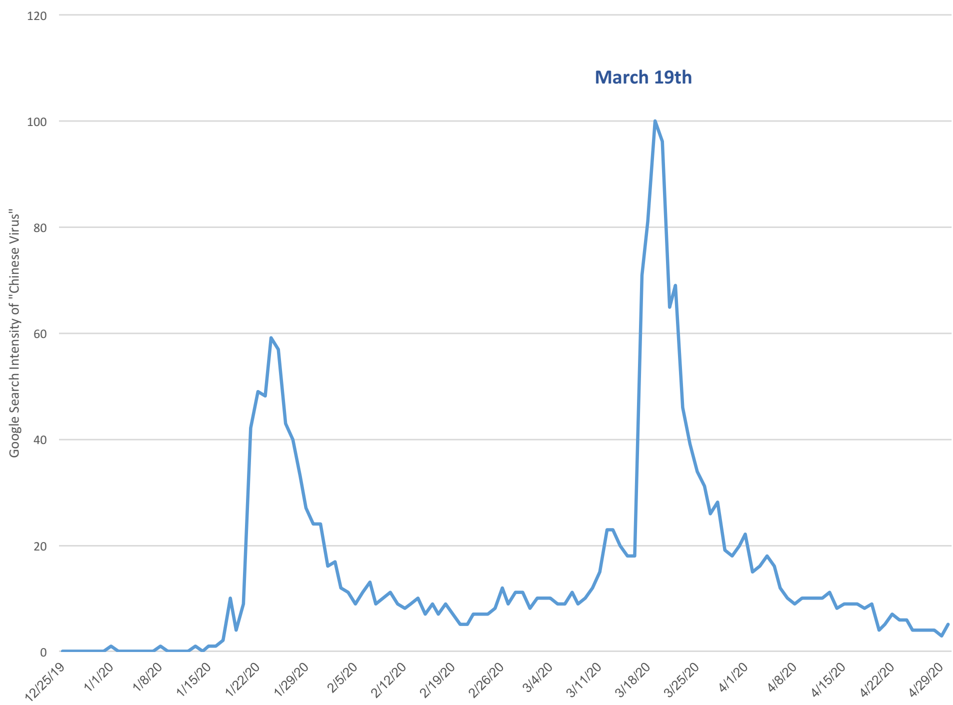


Figure A.3: President Trump tweets that contain the term "Chinese Virus"

This figure presents a screenshot from Trump Twitter Archive, with the search term "Chinese Virus." President Trump authored 8 tweets with the term between March 16 and March 22, 2020, each of which occuring near the peak of Google Search Intensity noted in Figure A.2.

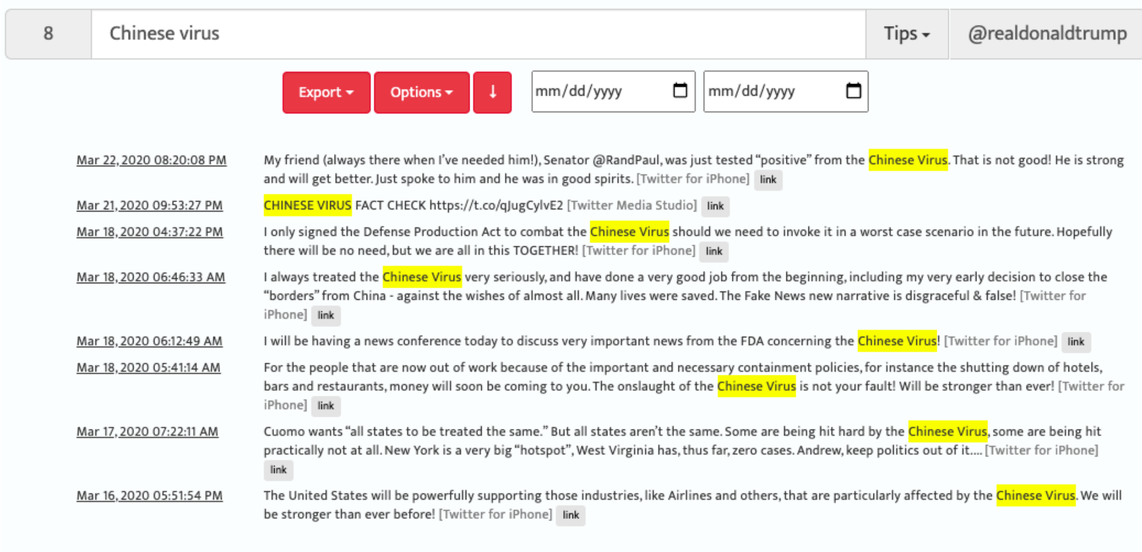
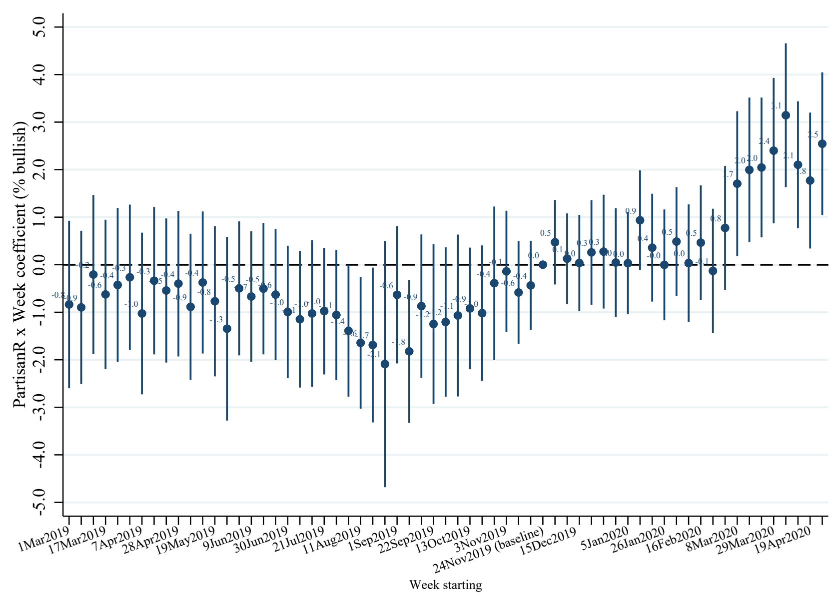


Figure A.4: Partisan Republicans are more Optimistic than Other Users during COVID – Weekly Estimates

This figure presents the weekly timing of the emergence of partisan Republican optimism during COVID. The figures present the time series of estimated coefficients on the interaction between an indicator for whether a user is a partisan Republican and weekly fixed effects. These estimates are drawn from a weekly version of equation (2), which includes user-stock fixed effects. The sample follows Table 4 (March 2019 through April 2020). The vertical bars illustrate 95% confidence intervals with standard errors clustered by user. Panel (a) presents the estimated coefficients on the sample of all stocks. Panel (b) presents the estimated coefficients drawn from the sample of S&P500 stocks.

(a) All Stocks




(b) S&P500 Stocks

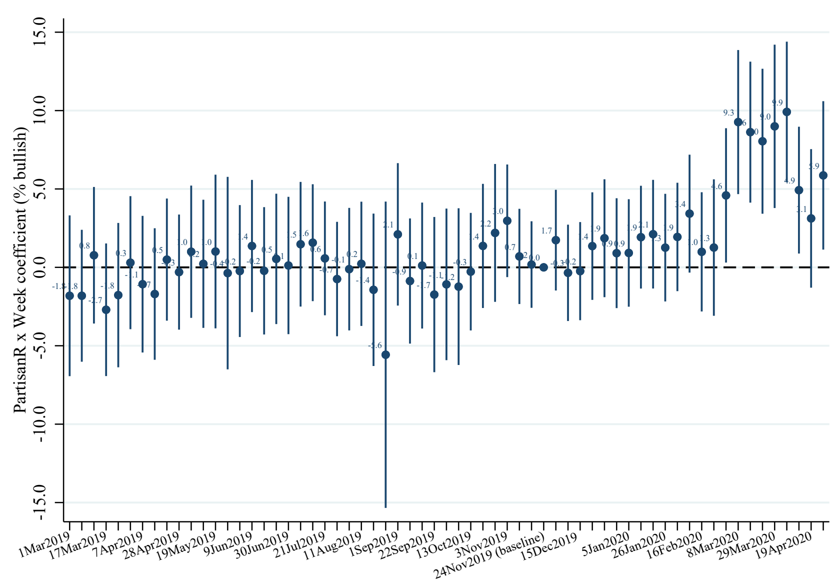


Figure A.5: Differential Partisan Republican pessimism about US-listed Chinese stocks: monthly estimates since 2018

This figure presents the time series of estimated coefficients on the triple interaction between an indicator for Partisan Republican users, monthly fixed effects, and whether the stock is a U.S.-listed Chinese firm. These estimates are drawn from the monthly version of the specification in equation (3), which includes user-stock fixed effects. The sample runs from January 2018 through April 2020. The vertical bars illustrate 95% confidence intervals with standard errors clustered by user.

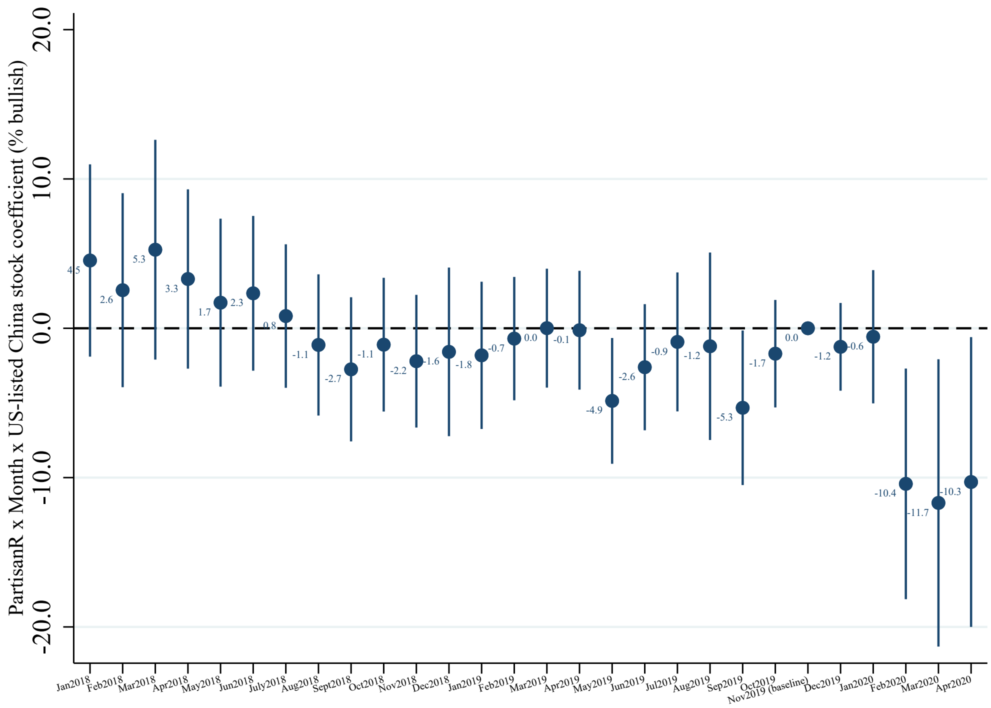
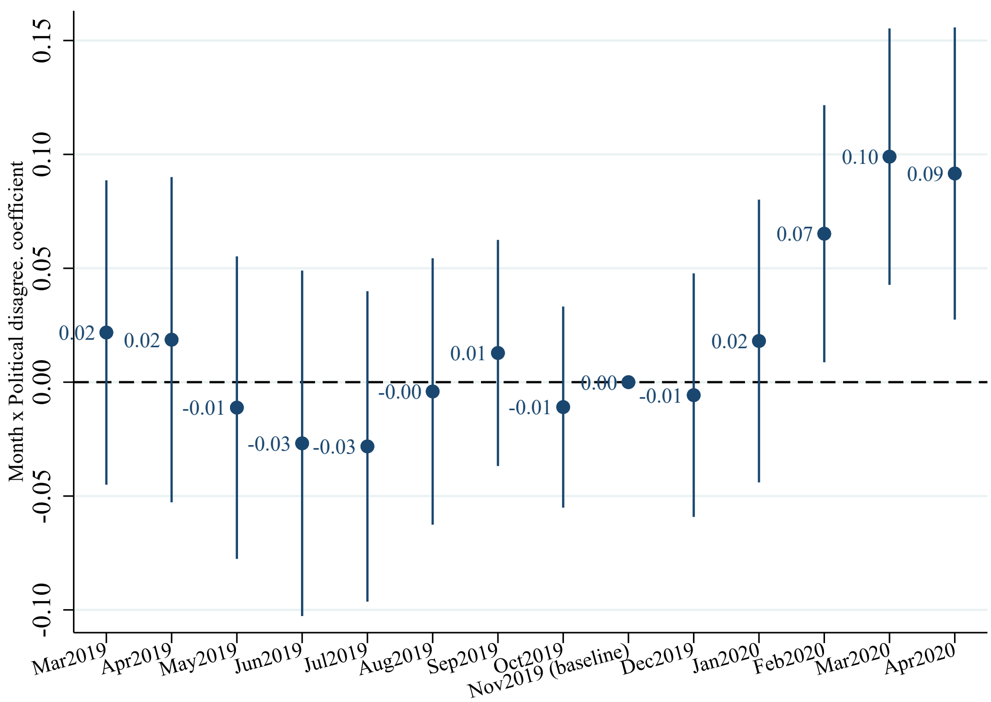


Figure A.6: Partisan Disagreement and Abnormal Trading Volume – Leads and Lags Plot

This figure presents the monthly timing of the emergence of the relationship between partisan disagreement and abnormal trading volume. The figure presents the time series of estimated coefficients on the interaction between $PartisanDisagree_{s,t}$ and monthly fixed effects. These estimates are drawn from a regression following equation (5), which includes user-stock fixed effects, number of impression fixed effects, and date fixed effects. The sample follows Table 6 (March 2019 through April 2020). The vertical bars illustrate 95% confidence intervals with standard errors double clustered at the stock and day levels.



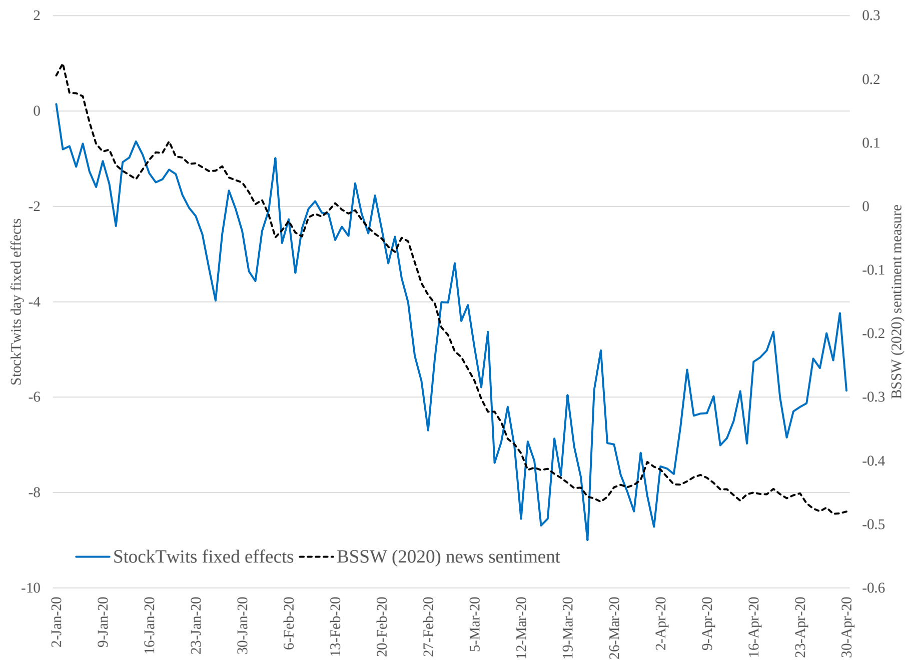
## Table A.6: List of Stocks with Largest Percentage Loss (Jan 1 – Mar 23)

This table reports the 10 S&P500 firms that had the worst stock market performance from January 1, 2020 through the S&P500 market bottom on March 23, 2020.

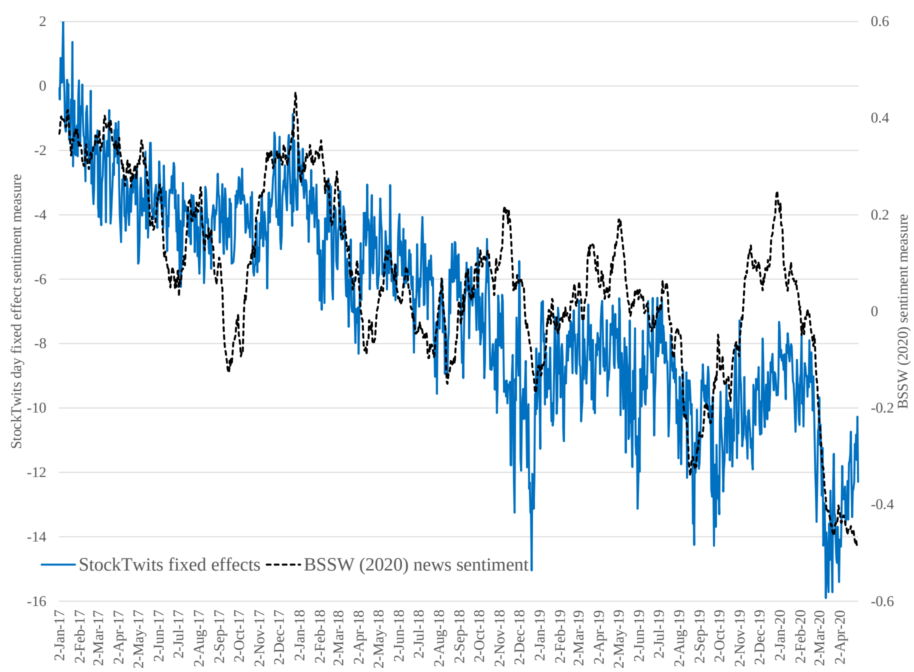
| Company | Return (Jan 1 – Mar 23) |
|---|---|
| Halliburton Co | -78.3% |
| Devon Energy Corp | -75.9% |
| USX Corp | -75.2% |
| Kohl's Corporation | -73.2% |
| MGM Resorts International | -72.3% |
| Macy's Inc. | -70.3% |
| United Airlines | -70.2% |
| Schlumberger Ltd. | -67.6% |
| Boeing Co | -67.4% |
| Valero Energy | -64.8% |

Figure A.7: Comparing StockTwits optimism and News Sentiment

This figure presents estimated daily fixed effects following equation 1 from January-April 2020 (top panel) and from January 2017-April 2020 (bottom panel). The omitted (reference) period is January 1, 2020 (top panel) and January 1, 2017 (bottom panel). The figure also includes the daily news sentiment measure developed in Shapiro, Sudhof, and Wilson (Forthcoming) and extended in Buckman et al. (2020) (labeled BSSW (2020) below, available here). The correlation between the two series is 0.75 (top panel) and 0.79 (bottom panel). The time series of coefficients for the bottom panel is available here:
http://www.tonycookson.com/data-and-programs




(a) Time Series of Daily Fixed Effects starting on Jan 1, 2020






(b) Time Series of Daily Fixed Effects starting on Jan 1, 2017