

Cookson, J. Anthony; Engelberg, Joseph; Mullins, William

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

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

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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, which explains 20% of the increase in stock turnover during the pandemic.

*Cookson is at the Leeds School of Business at University of Colorado-Boulder (tony.cookson@colorado.edu). Engelberg and Mullins are at the Rady School of Management, UC San Diego (jengelberg@ucsd.edu). We are grateful for comments from Asaf Bernstein, Steve Billings, Winston Dou, Diego Garcia, Yuval Rottenstreich, and Antoinette Schoar.

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 investors' 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 (Bartels, 2002; Milner and Judkins, 2004; Gerber and Huber, 2009) 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). However, it is 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 form accurate expectations about a firm's prospects, then their political identity should be ignored when forming these expectations. Nevertheless, we find that the differences in investor beliefs between partisan Republicans and other investors are pervasive and sustained throughout the COVID-19

period.

We employ novel data from StockTwits, a popular investor social network, to measure partisan identity at the individual level, and observe investment beliefs at the 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 COVID-19. 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 moves together with 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 approximately 2 percentage points across all stocks and 5 percentage points

¹We also validate our individual classification of partisan investors 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.

for firms in the S&P500. Because we include user-security fixed effects, these estimates reflect changes in 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 lost value during the COVID-19 period in comparison to other users.

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; 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, motive for their beliefs.

Our analysis primarily focuses on how partisan investment beliefs diverge during the COVID-19 period, but our measure of partisan Republican sentiment accurately reflects

²Our 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.

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.

The political divide in investor beliefs during COVID-19 coincided with an enormous increase in trading volume: at the height of the pandemic, abnormal daily stock turnover increased by approximately 36%. In our final set of tests, we measure partisan disagreement at the daily stock level and relate abnormal trading volume to partisan disagreement among the cross-section of stocks in a difference-in-difference framework. Our estimates imply a tight connection: a one standard deviation increase in partisan disagreement during the pandemic leads to 7% more abnormal stock turnover, which is 20% of its increase during the COVID-19 period, and is greater than the trading implied by a standard deviation increase in overall disagreement. The finding that partisan disagreement contributed significantly to the sharp increase in stock market turnover during the pandemic also suggests that the differences in partisan beliefs extracted from StockTwits reflect partisan disagreement among a broad set of investors.

Our central contribution is to show an individual link between partisan identity and investor beliefs. Our findings most closely relate to [Meeuwis et al. \(2019\)](#), which shows that individuals in Republican areas invest their retirement assets more aggressively after the Trump election, consistent with partisan investment optimism. In addition, [Mian, Sufi, and Khoshkhoh \(2017\)](#) present survey evidence that declared Trump supporters are more

optimistic about the economy, but that they do not change household spending. In contrast to this evidence from the 2016 election, which ushered in a different policy regime favored by Republicans, COVID-19 led investors to face unprecedented uncertainty about the likelihood of various economic policy scenarios (e.g., [Baker et al. 2020a](#)). The evidence we present regarding the importance of political identity in forming investment beliefs during the pandemic suggests that people default to core identities, such as political affiliation, when facing significant uncertainty.³

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 three advantages. First, 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.⁴ Second, we show important *cross-sectional* differences in partisan belief formation: our finding of Republicans’ pessimism on Chinese stocks shows that these partisan investor beliefs do not merely reflect general economic optimism, but a more nuanced 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 a non-informational factor drives differential belief up-

³Related to this point, 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.

⁴When studying the beliefs of individual investors, 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. \(2019\)](#) address this measurement concern using robustness tests that rule out hedging needs and initial differences, and shows parallel trends. Further, they complement with evidence from the Michigan Survey of Consumer Confidence that shows that Republicans are more optimistic about the national economy, but not about their own economic situations.

dating, we provide new evidence that investors apply different models to interpret market information (e.g., see [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](#)).

Though both political and investment beliefs have been studied in the context of COVID-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 apply partisan labels to StockTwits users, and provide empirical context for our study of the connection between partisan identity 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 proclaims 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 provide a similar function 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 the stocks: Both [Cookson and Niessner \(2020\)](#) and [Giannini, Irvine, and Shu \(2018\)](#) show that different proxies for dispersion of sentiment sensibly relate to market-level trading volume. Owing to its unique data features, StockTwits has attracted recent academic attention (e.g., see [Cookson, Engelberg, and Mullins \(2020\)](#) on selective exposure to information, [Cookson and Niessner \(2020\)](#) and [Giannini, Irvine, and Shu \(2018\)](#) on various aspects of disagreement, and [Giannini, Irvine, and Shu \(2017\)](#) on local information advantage).

We have the full history of messages posted to StockTwits through April 2020. As in [Cookson and Niessner \(2020\)](#), we restrict attention to messages that mention only one ticker to focus on sentiment that can be directly linked to a particular 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 5.3 million messages by 119,434 unique users regarding 1,042 unique securities (stocks, indexes and other assets). Aggregating to the security-user-day level, our analysis sample contains nearly 2.3 million observations. Our specifications with user-security fixed effects drop singleton observations (e.g., users who post 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 useful feature of StockTwits from the standpoint of academic research is that the platform encourages users to self-classify whether their sentiment is bullish or bearish for each message. To self-classify a message as bullish or bearish, a user simply clicks on a prominently displayed button on the StockTwits user interface before posting (e.g., see Panel (a) of Figure 1).

StockTwits messages reflect genuine investor beliefs at the time of posting. To maintain the reliability of reputations on StockTwits, old messages cannot be deleted. This feature both preserves the incentives of users to post truthful best forecasts for their follower-base, and 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. For two posts about Apple (symbol \$AAPL), Panels (b) and (c) of Figure 1 present examples of a bullish post and a bearish post.

2.2 Identifying Partisan Investors in StockTwits

In addition to the self-classified sentiment about investments, StockTwits users sometimes discuss other topics, like politics. These additional posts are useful for measuring individual users’ partisan affiliation. To identify partisan Republican posts on StockTwits, we follow the [Gentzkow and Shapiro \(2010\)](#) study of media slant to identify a list of keywords that flag posts as political and Republican.⁵

We begin by considering 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 (up to three words

⁵We follow a similar approach to identify Partisan Democrats. However, there are many fewer Democrats in our sample, consistent with the findings of [Ke \(2019\)](#), leading us to have less power to say much about the opinions of partisan Democrats. For this reason, our analysis focuses on differences of opinions between partisan Republicans and other users who could be either non-partisan, or partisan Democrats.

in length) 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 use 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.

Panel (a) of Table 2 contains the final list of partisan Republican keywords, which contain distinctively partisan Republican language, such as “Liberal Media” and “Russia Hoax.” From reading the posts flagged by this list of keywords, the vast majority of flagged posts contain unambiguous partisan Republican statements. We report several examples of flagged partisan Republican messages in Panel (b) of Table 2. We classify a *user* as a partisan Republican if they make or like at least three of these flagged partisan Republican messages.

Panel (b) of Table 1 presents summary information on our classification procedure. Applied to the 179 million StockTwits messages prior to our sample period, a total of 31,361 messages contain Republican keywords (only 9,388 are stamped with bullish or bearish sentiment). Out of the 780,000 users who were active on StockTwits prior to 2020, we identify 18,975 users who make or like at least one partisan Republican message. However, restricting to users who like at least three messages, we identify 4,716 users as partisan Republican. The restriction of showing approval for multiple partisan Republican messages helps ensure that the individuals we identify are truly and persistently partisan Republican.

Restricting attention to the sample period (Oct 2019–Apr 2020), our sample contains 2,331 Republican-identified users and 117,103 other users who were active during this period. Of course, many of these other users are also Republicans who do not regularly use or like Republican language on StockTwits. By comparing a group of Republicans to a group that contains a mixture of Republicans, non-partisans and Democrats, our estimates likely understate the true size of the partisan gap.

Although partisan Republicans only comprise 2% of the users in our sample, they tend to be more active users on the platform, posting 575,776 sentiment-stamped messages during the sample period, which is approximately 10% of the messages in our sample. To be clear, these sentiment stamped messages are “out of sample” in two respects: First, partisan Republican users are identified via pre-2020 messages, distinctly prior to our COVID-19 sample period. Second, the sentiment-stamped messages in our analysis sample rarely contain political language. Because our classification’s aim is to assign partisanship at the user level, we do not need to rely upon the rare combination of messages that contain sentiment and political statements.⁶

2.3 Politicized Stock Markets

Since the 2016 Presidential Election, the connection between political identity and beliefs about the stock market has become more important. President Trump has tweeted about the “stock market” 130 times from the 2016 Election through May 24th, 2020, often citing the rise of the stock market as a political accomplishment, or cheering stock market milestones.⁷ 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 for a broader sample that begins in 2015. To construct a time series of sentiment by partisan affiliation we estimate the following specification using data from January 2015 onward:

⁶We observe that 9,388 of the flagged messages from the classification period (2015 through 2019) are partisan messages *and* are also sentiment stamped. These overt partisan statements about stocks, thus, comprise an insignificant fraction of messages relative to the sample of 575,776 sentiment-stamped messages by partisan Republicans.

⁷The content of the tweets can be found at the online Trump Twitter Archive, available here (<https://bit.ly/3cBxbmN>).

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

in which the dependent variable is an indicator for whether user j is bullish about stock 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. γ^B are month fixed effects for the baseline group of non-partisan Republican users, while the vector of fixed effects γ^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 (as identified by our classification procedure) 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.” Consistent with the points of divergence we observe in Panel (a), Google Search Intensity of “Trump and Stock Market” 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. Aside from providing evidence that confirms the timing of these events, these spikes in Google attention suggest that investors more broadly, not just on StockTwits, are associating the stock

market with politics at these key moments.⁸

2.4 Partisan Investor Beliefs during COVID-19

Although the broader connection between politics and investor beliefs is of general interest, 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 remarkably 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.

⁸President 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!*” This was in reaction to a market decline that appeared driven by fears that inflationary pressure would generate a reaction by the Federal Reserve. Note however, that 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 \(1995\)](#).

3 Evidence on Partisan Investor Beliefs

This section presents regression evidence on 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:

$$Bull_{s,j,t} = \eta_{s,j} + \gamma_m^B + \sum_m \beta_m^R (1 \{month = m\} \times \mathbb{1}PartisanR_j) + \varepsilon_{s,j,t} \quad (2)$$

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 (γ_m^B) yield time-varying sentiment estimates for the baseline group. The coefficients of interest are β_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 identifier, 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 December 31, 2019. To evaluate broad 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 frame we obtain similar qualitative

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 over 5 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 3.2 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&P500.⁹

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 differ-

⁹Figure A.3 in the Appendix presents an analogous plot at the weekly frequency. Specifically, we present $\mathbb{1}_{PartisanR_j} \times$ week interactions from a leads-and-lags specification based on the sample used in our main tests (October 2019 through April 2020).

ence specification of the following form:

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

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).¹⁰ $\mathbb{1}PartisanR_j$ 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 December 31, 2019, (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.

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 country of origin.¹¹ While some com-

¹⁰Though 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.

¹¹In support of this we report two figures in the Appendix. In Figure A.1, we present the daily time series for Google Search Intensity of 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 virus that had not yet been named COVID-19 at the time. The second peak was around a series of tweets by President Trump that mentioned

mentators called this terminology xenophobic (Vazquez, 2020), it reflected a partisan Republican negativity toward China in recent years, consistent with the US-China Trade War leading to a greater divergence in sentiment between partisan Republicans and other users (e.g., see Figure 2).

Given the sharp political divide on China during the COVID-19 period, it is natural to evaluate whether these general political beliefs also shape investor beliefs about Chinese firms in the financial context. To evaluate this, 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 over 8 percentage points more pessimistic about Chinese firms during the COVID-19 period (March and April, 2020) 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 1.6 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 $\mathbb{1} Covid_t \times \mathbb{1} PartisanR_j$.

In addition, to show when this negativity emerged, we estimate a version of equation (3) that replaces the $Covid_t$ indicator with a series of weekly fixed effects. Figure 5 presents the dynamic plot of the triple interaction coefficient estimates with 95% confidence intervals. The dynamic plot indicates no significant pre-trends from March 2019 through early February 2020. The point estimates give some indication of pessimism by parti-

the term “Chinese Virus” (March 19th) – e.g., see Figure A.2 for a screenshot of these tweets from Trump Twitter Archive. The second peak is arguably when China’s role became politicized in the U.S., and this is coincident with the largest partisan differences in beliefs about Chinese stocks (see Figure 5).

san Republicans in early February, as cases grew rapidly in China, but the triple difference estimate becomes even larger in mid-March when China became most politicized. It is noteworthy that the partisan Republican pessimism about Chinese stocks became strongest in March when the health crisis subsided in China and when Chinese firms began to operate again. This timing suggests a political, rather than economic, motive for these partisan differences in investment beliefs.

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. Specifically, we estimate that partisan Republicans are 5.8 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 disagreement among partisans during the pandemic.

3.2.3 Optimism about Stocks that Lost Value

Finally, another possible explanation for 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.¹²

Table 4 presents the results from estimating this specification in column (3), restricting attention to S&P500 stocks where the partisan differences in opinion are clearest. Consistent with partisan Republican belief in a faster and more complete recovery, we estimate that partisan Republicans are around 10.9 percentage points more optimistic about the worst performing firms during the COVID-19 period (Table A.1).¹³ 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.¹⁴

¹²Unlike 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.

¹³The estimated coefficient for the triple interaction equals 13.9%, multiplied by the worst performing firm's loss of 78.3% (Halliburton), which equals our reported magnitude of 10.9.

¹⁴To give context for this contrarian preference, Table A.1 reports the 10 worst-performing S&P500 stocks for the period from January 1st through the market bottom on March 23rd. As one might expect, the stocks that lost the most value during this period are heavily focused in the energy sector (Halliburton and Schlumberger), airlines (United Airlines and Boeing Inc), and major retail (Macy's and Kohl's).

4 Partisan Disagreement and Stock Turnover

In this section, we connect differences in partisan investor beliefs to daily stock turnover. Although disagreement is a standard driver of trading activity, it is of particular interest to examine turnover during the COVID-19 period, when turnover rose markedly.

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 in our other tests, daily stock turnover sharply increased around the beginning of March 2020 and remained high throughout the COVID-19 period. In addition to this striking 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 need to construct a measure of difference of opinion between partisan Republicans and other users. Following the approach in [Cookson and Niessner \(2020\)](#) for the two group case, we measure partisan disagreement at the stock-day level as:

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

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:

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

where the dependent variable $AbnormalLogTurnover_{s,t}$ is the abnormal log turnover for stock s on day t .¹⁵ $\mathbb{1}Covid_t$ 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 facilitate interpretation, the disagreement measures are standardized to have 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

¹⁵Following 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).

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 36.1% 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 16.4%.

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 5.2% 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 8.5 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 ($est = -0.005$, $se = 0.009$). However, during the pandemic, a standard deviation increase in partisan disagreement is associated with 7.1% greater stock turnover, which is 20% of the baseline rise in stock turnover during the COVID-19 period (column (1)), and 36% of the effect of attention on turnover.¹⁶ The estimated magnitude of the $\mathbb{1}Covid_t \times Partisan Disagree_{s,t}$ coefficient is slightly greater than the baseline coefficient for overall disagreement (0.071 versus 0.056). 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.

¹⁶Referencing columns (1) and (2), the inclusion of number of impressions fixed effects reduces the magnitude of the estimate on $\mathbb{1}Covid_t$ by 19.7 percentage points. The estimated magnitude on the $\mathbb{1}Covid_t \times Partisan Disagree_{s,t}$ term is 7.1, which is 36% of this reduction of 19.7 percentage points.

The remaining columns show that these inferences about the relation between partisan disagreement and 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 trading volume that is unlikely to be driven by other factors. Our main coefficient of interest is β_5 on the $\mathbb{1}Covid_t \times Partisan\ Disagree_{s,t}$ term. This coefficient effectively contrasts the abnormal trading volume of high partisan disagreement stocks to that of low partisan disagreement stocks, before versus during the COVID-19 period.¹⁷ 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 that have identical financial attention, with the inclusion of 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.

In summary, partisan differences in investment beliefs bear an economically important relation 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 as well.

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. Consistent with the narrative that partisanship shapes investor beliefs, Republican views follow a nuanced

¹⁷Figure A.4 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.

pattern: they are more optimistic about stocks that recently lost value but more pessimistic about US-listed Chinese stocks. The partisan disagreement we document explains 20% 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 to cite a few 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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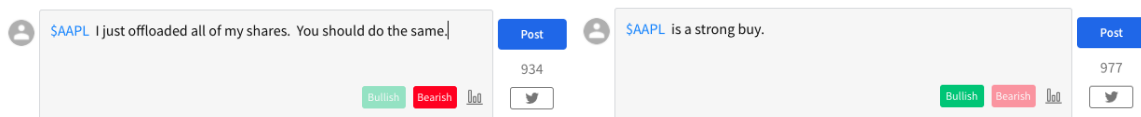
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Figures

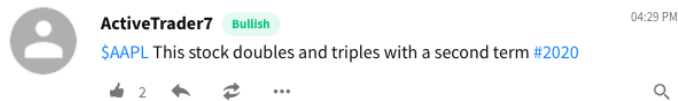
Figure 1: Contextual Examples of StockTwits Posts and Sentiment

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

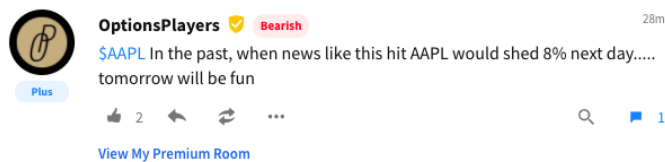
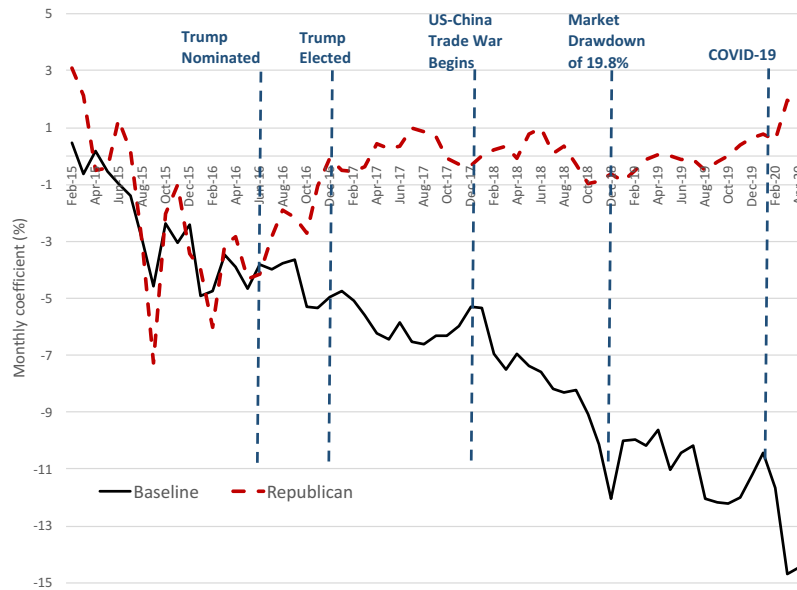


Figure 2: Optimism for Partisan Republicans versus Other Users (Jan 2015 – Apr 2020)

This plot shows how differences in optimism between Partisan Republicans and other StockTwits users evolve over time since 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) Monthly Time Series of Sentiment Fixed Effects



(b) Google Search Intensity for “Trump and Stock Market”

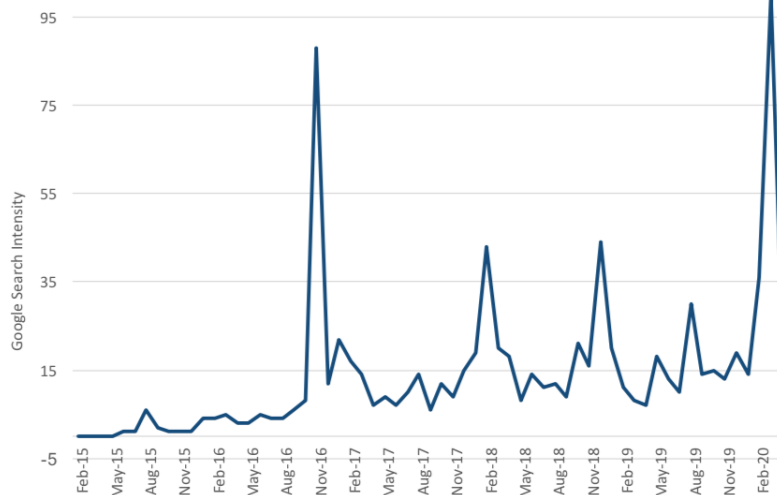
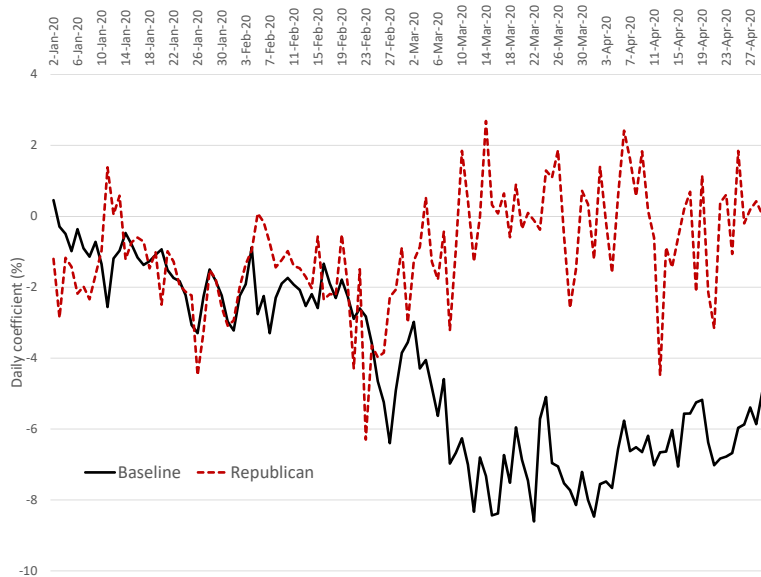


Figure 3: Optimism for Partisan Republicans versus Other Users Over Time – COVID Period

This plot shows how differences in optimism between Partisan Republicans and other StockTwits users evolve over time since January 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. Panel (b) presents the rolling one-week average of Google Search Intensity for “Trump and Stock Market” for the same COVID period (January 2020 to April 2020).

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



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

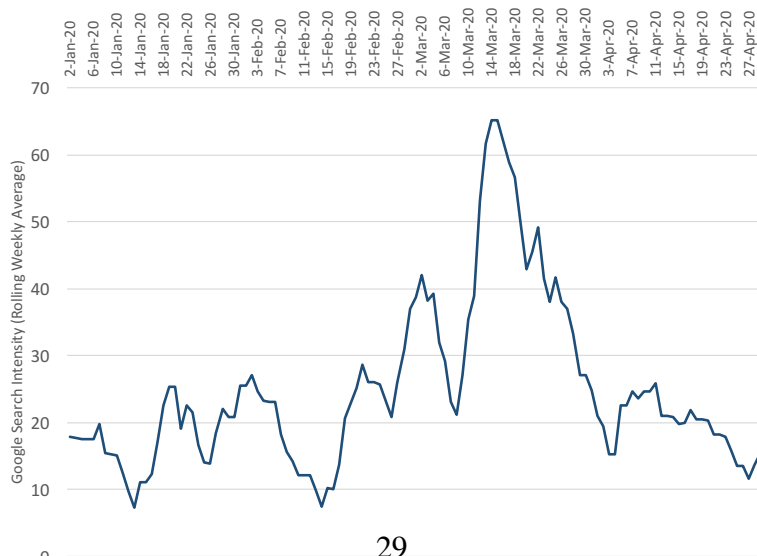
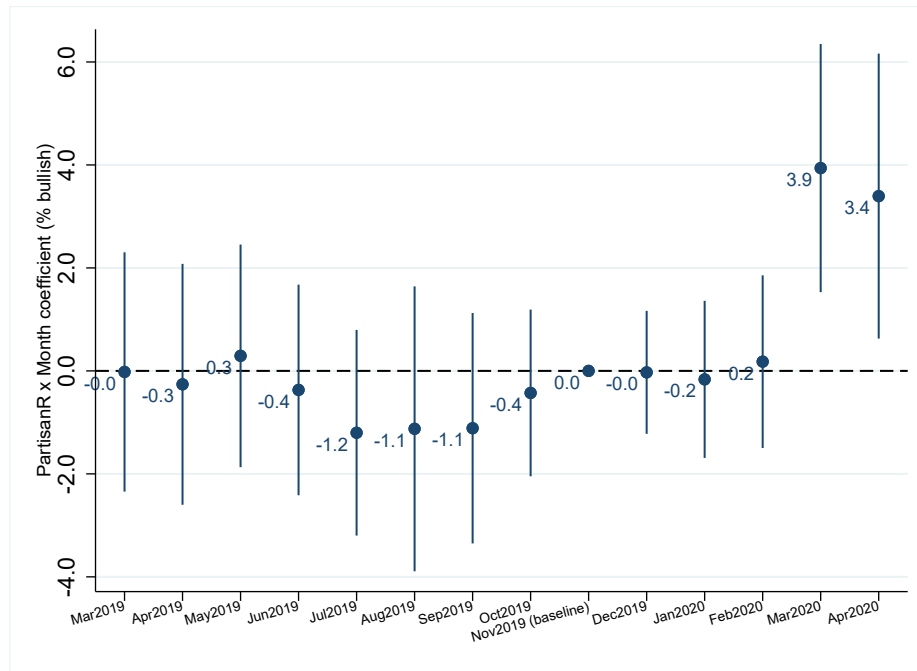


Figure 4: Partisan Republicans are More Optimistic than Other Users During COVID

This figure presents the timing of the emergence of Partisan Republican optimism during COVID. The figures display 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 runs from 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 2019. Panel (b) presents the estimated coefficients on the subset of S&P500 stocks.

(a) All Stocks, excluding Small Cap Stocks



(b) S&P500 Stocks

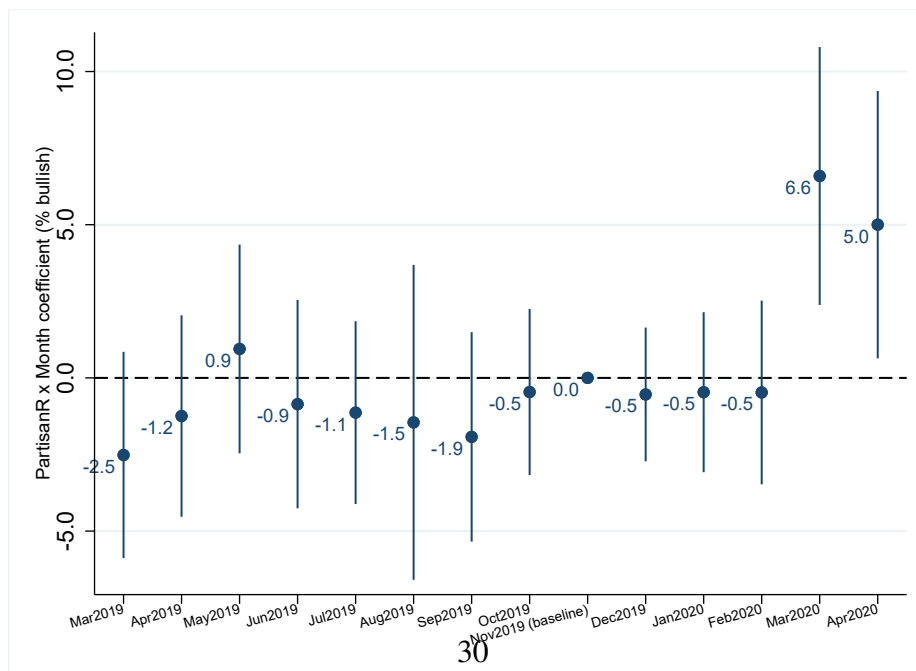


Figure 5: Partisan Republicans are Pessimistic about Chinese Stocks During COVID

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 US-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 runs from March 2019 through April 2020. The vertical bars illustrate 95% confidence intervals with standard errors clustered by user.

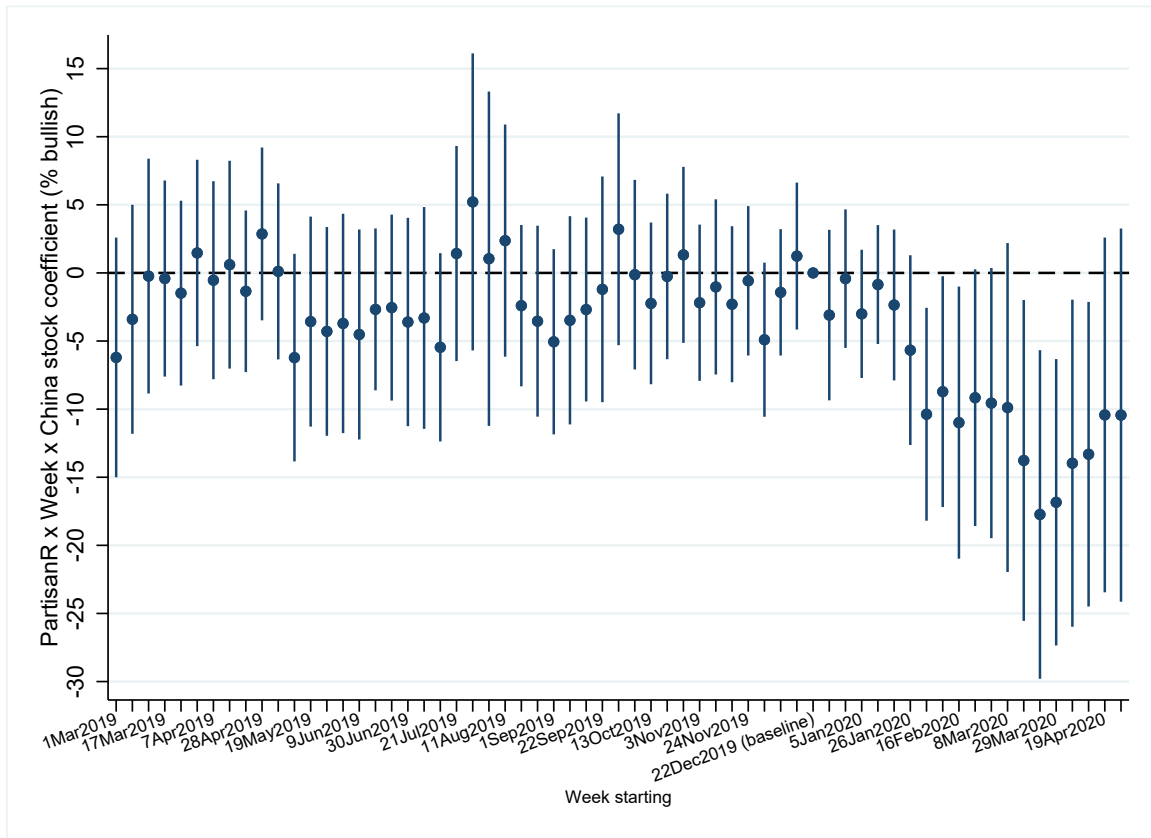
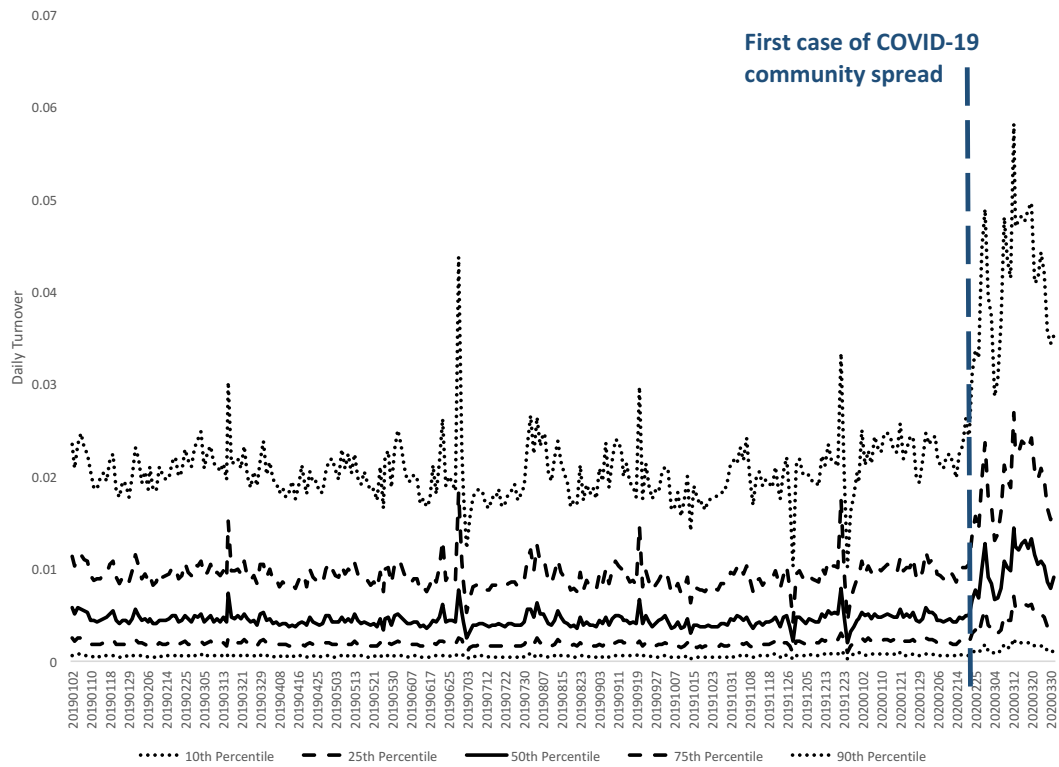


Figure 6: Percentiles of Daily Stock Turnover

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 dashed 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 about the StockTwits data. Panel (a) presents counts of the various units of observations that make up of our data – users by partisan affiliation, securities, message sentiment and days, which provide 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 the level of activity of these users in the analysis sample.

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

| | Totals | Totals | |
|--------------------------------|-----------|--------------------------|-------|
| Sentiment Messages | 5,351,351 | Days | 213 |
| Bullish | 4,298,445 | Pre-COVID | 152 |
| Bearish | 1,052,906 | COVID | 61 |
| Users | 119,434 | Securities | 1,042 |
| Republican | 2,331 | CRSP (e.g., Tesla) | 945 |
| Other users | 117,103 | Non-CRSP (e.g., Bitcoin) | 97 |
| User-Securities-Sentiment Days | 2,282,605 | | |
| Republican | 199,604 | | |
| Other users | 2,083,001 | | |

(b) Message and User Classification Details

| | |
|--|-------------|
| Messages Considered (pre-2020) | 179,229,881 |
| Messages that contain Republican keywords | 31,361 |
| Users Considered (pre-2020) | 780,909 |
| Users who made or liked <i>any</i> Republican message | 18,975 |
| Republican-identified users (i.e., liked or made 3+ Republican messages) | 4,716 |
| Republicans' Posting (Oct 2019-Apr 2020) | |
| Republican-identified users active | 2,331 |
| Sentiment stamped messages by Republicans | 575,776 |
| Republican observations (User-Security-Days) | 199,604 |

Table 2: Classification of Partisan Republican Users

This table presents contextual information regarding our classification of Partisan Republican users. 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 five example tweets that are flagged by this list of keywords. In the iterative process we use to develop this keyword list, we seed the list of 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. A StockTwits user is identified as a Partisan Republican if they post or like at least three tweets that contain any of these Partisan Republican keywords.

(a) Partisan Republican Keywords

| | |
|-------------------|---------------------|
| "#MAGA" | "The Liberals" |
| "Russia Hoax" | "Russian Collusion" |
| "#TRUMP2020" | "Stupid Dems" |
| "Hussein Obama" | "Leftists" |
| "Obummer" | "Trump Derangement" |
| "Fake News Media" | "The Socialist" |
| "Crooked Hillary" | "MAGA 2020" |
| "The Snowflakes" | "The Commie" |
| "Liberal Media" | "Libtard" |
| "Libs" | "Stupid Democrats" |
| "Trump Hater" | "Sleepy Joe" |

(b) Examples of Partisan Republican Tweets

| | |
|--------------|---|
| Oct 10, 2018 | "Fox News... This crash will teach those libtards!! \$spy |
| Oct 27, 2019 | "Therapy bro, Trump derangement syndrome is no joke. Get some meds" |
| Nov 15, 2019 | "\$SPY I don't think this is related to China, rather the impeachment hearings being a total flop. Liberal media would never say so but this is pricing in 5 more years. Just a thought." |
| Jul 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" |
| Jan 28, 2019 | "\$SPY BULLISH #MAGA" |

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 an investor j declares as bullish about stock s on day t . The specification includes monthly fixed effects, and their interactions with an indicator for whether a user is a Partisan Republican based on the text of their posts before 2020. 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. User-security fixed effects are included in all regressions. Column (1) is estimated on the full set of 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, while 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: $\mathbb{1} \times 100$ if Bull _{s,j,t} | | | |
|---|--|--------------------|-----------------------------|---------------------------|
| | (1) All securities | (2) Only stocks | (3) Mkt cap > NYSE p(25) | (4) Only S&P500 stocks |
| Oct2019 | 0.1 [0.2] | 0.4** [0.2] | -0.4 [0.3] | -1.4 [1.3] |
| Nov2019 (baseline) | 0.0 [.] | 0.0 [.] | 0.0 [.] | 0.0 [.] |
| Dec2019 | 0.4*** [0.1] | 0.3** [0.1] | 0.4** [0.2] | 0.5 [0.7] |
| Jan2020 | 0.8*** [0.2] | 0.4*** [0.2] | 0.9*** [0.3] | 1.2 [1.3] |
| Feb2020 | -0.5*** [0.2] | -0.9*** [0.2] | -0.8** [0.3] | -1.5 [1.3] |
| Mar2020 | -3.5*** [0.3] | -3.3*** [0.3] | -5.6*** [0.5] | -7.3*** [2.5] |
| Apr2020 | -3.5*** [0.2] | -3.6*** [0.2] | -5.4*** [0.4] | -6.2*** [2.2] |
| $\mathbb{1}$ PartisanR _j x Oct2019 | -0.8 [0.5] | -0.9* [0.5] | -1.1 [0.9] | -1.4 [1.4] |
| $\mathbb{1}$ PartisanR _j x Dec2019 | 0.0 [0.4] | 0.1 [0.4] | -0.1 [0.6] | -0.7 [1.2] |
| $\mathbb{1}$ PartisanR _j x Jan2020 | 0.1 [0.5] | 0.2 [0.4] | -0.1 [0.7] | -0.7 [1.6] |
| $\mathbb{1}$ PartisanR _j x Feb2020 | -0.1 [0.5] | -0.0 [0.5] | -0.2 [0.8] | -1.2 [1.6] |
| $\mathbb{1}$ PartisanR _j x Mar2020 | 1.6** [0.8] | 1.8*** [0.6] | 3.2*** [1.1] | 4.9** [2.0] |
| $\mathbb{1}$ PartisanR _j x Apr2020 | 1.4* [0.8] | 1.9*** [0.7] | 3.2*** [1.1] | 4.0** [2.0] |
| # observations | 1,956,662 | 1,676,915 | 646,571 | 252,213 |
| # clusters (users) | 75,832 | 69,388 | 37,702 | 148 |
| R ² | 0.75 | 0.77 | 0.76 | 0.74 |
| Uncond. mean of dependent var. | 81.5 | 84.9 | 76.2 | 73.2 |
| User-Security FE | Y | Y | Y | Y |

Table 4: Heterogeneity in Partisan 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 Covid variable is an indicator equal to one in March and April 2020; the $PartisanR_j$ indicator is equal to one for users identified as partisans based on the text of their posts in 2018 and 2019. 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 only (148 stocks). Standard errors clustered by user are reported in brackets; ** and *** indicate statistical significance at 5% and 1%.

| | Dependent variable: $\mathbb{1} \times 100$ if Bull $_{s,j,t}$ | | | |
|---|--|---|---|---|
| | (1) Interaction: $\mathbb{1}$ if China stock | (2) Interaction: $\mathbb{1}$ if S&P500 stock | (3) Interaction: market model R^2 | (4) Interaction: 1 month returns (S&P500 stocks) |
| $\mathbb{1}$ in Covid $_t$ period | -3.4*** [0.2] | -3.0*** [0.2] | -2.3*** [0.2] | -6.1*** [0.6] |
| $\mathbb{1}$ Covid $_t$ x $\mathbb{1}$ Partisan R_j | 1.9*** [0.6] | 0.7 [0.5] | 0.4 [0.5] | 6.2*** [1.8] |
| $\mathbb{1}$ Covid $_t$ x $\mathbb{1}$ Interaction $_s$ | -1.4** [0.6] | -3.4*** [0.6] | | |
| $\mathbb{1}$ Covid $_t$ x $\mathbb{1}$ Partisan R_j x $\mathbb{1}$ Interaction $_s$ | -8.2** [4.1] | 5.8*** [1.7] | | |
| $\mathbb{1}$ Covid $_t$ x market model R_s^2 | | | -12.2*** [1.4] | |
| $\mathbb{1}$ Covid $_t$ x $\mathbb{1}$ Partisan R_j x market model R_s^2 | | | 13.4*** [4.1] | |
| Month return $_{s,t-1}$ | | | | 6.2*** [1.9] |
| $\mathbb{1}$ Covid $_t$ x month return $_{s,t-1}$ | | | | -5.1*** [1.9] |
| $\mathbb{1}$ Partisan R_j x month return $_{s,t-1}$ | | | | 6.1 [4.9] |
| $\mathbb{1}$ Covid $_t$ x $\mathbb{1}$ Partisan R_j x month return $_{s,t-1}$ | | | | -13.9*** [5.3] |
| # observations | 3,036,393 | 3,036,393 | 2,943,488 | 462,821 |
| # clusters (users) | 93,045 | 93,045 | 91,649 | 26,737 |
| R^2 | 0.75 | 0.75 | 0.75 | 0.70 |
| Uncond. mean of dependent var. | 84.1 | 84.1 | 84.0 | 73.2 |
| User-Security FE | Y | Y | Y | Y |

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.

| | Mean | Median | Std. dev. | N obs. |
|--|--------|--------|-----------|--------|
| Abnormal log turnover _{s,t} | 0.460 | 0.215 | 1.191 | 82,753 |
| Overall Disagree _{s,t} | 0.045 | 0.262 | 0.981 | 82,753 |
| Partisan Disagree _{s,t} | 0.002 | -0.375 | 0.978 | 82,753 |
| Standard deviation of abnormal returns _{s,(t-5 to t-1)} | 0.051 | 0.031 | 0.089 | 82,753 |
| Cumulative abnormal returns _{s,(t-5 to t-1)} | 0.009 | -0.005 | 0.220 | 82,753 |
| Cumulative abnormal returns _{s,(t-30 to t-6)} | -0.005 | -0.036 | 0.429 | 82,753 |
| Number of Impressions _{s,t} | 30.707 | 13.000 | 55.152 | 82,753 |

Table 6: Partisan Disagreement and Daily Stock Turnover

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

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

$AbnormalLogTurnover_{s,t}$ 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 most recent month) for stock s . The Covid 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. Fixed effects (FE) for stock (permno) 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 $t - 1$. 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 Turnovers _{s,t} | | | | | |
|---|---|-------------------------|---------------------------|----------------------------|---------------------|----------------------|
| | (1) Just $\mathbb{1} Covid$ | (2) + #Impression FE | (3) + Overall Disagree | (4) + Partisan Disagree | (5) + Day FE | (6) + Controls |
| $\mathbb{1}$ in Covid _t period | 0.361*** [0.051] | 0.164*** [0.048] | 0.150*** [0.047] | 0.152*** [0.047] | — | — |
| Overall Disagree _{s,t} | | | 0.052*** [0.008] | 0.056*** [0.011] | 0.060*** [0.011] | 0.029*** [0.006] |
| $\mathbb{1} Covid_t \times Overall Disagree_{s,t}$ | | | 0.085*** [0.025] | 0.039 [0.029] | 0.025 [0.029] | -0.006 [0.018] |
| Partisan Disagree _{s,t} | | | | -0.005 [0.009] | -0.005 [0.009] | -0.005 [0.005] |
| $\mathbb{1} Covid_t \times Partisan Disagree_{s,t}$ | | | | 0.071*** [0.024] | 0.065*** [0.023] | 0.047*** [0.015] |
| Volatility of abnormal ret. _{s,(t-5 to t-1)} | | | | | | 0.027 [0.099] |
| Cum. abnormal ret. _{s,(t-5 to t-1)} | | | | | | -0.221*** [0.030] |
| Cum. abnormal ret. _{s,(t-30 to t-6)} | | | | | | -0.094*** [0.028] |
| Abnormal Log Turnover _{s,t-1} | | | | | | 0.509*** [0.015] |
| # observations | 87,191 | 82,778 | 82,778 | 82,778 | 82,778 | 82,753 |
| # clusters (stocks) | 880 | 876 | 876 | 876 | 876 | 876 |
| # clusters (days) | 295 | 295 | 295 | 295 | 295 | 295 |
| R ² | 0.29 | 0.61 | 0.61 | 0.61 | 0.63 | 0.76 |
| Uncond. mean of dependent var. | 0.435 | 0.460 | 0.460 | 0.460 | 0.460 | 0.460 |
| Stock FE | Y | Y | Y | Y | Y | Y |
| # of Impressions _{s,t} FE | . | Y | Y | Y | Y | Y |
| Day FE | . | . | . | . | Y | Y |

Internet Appendix to:

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

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

¹Cookson is at the Leeds School of Business at University of Colorado-Boulder (tony.cookson@colorado.edu). Engelberg is at the Rady School of Management, UC San Diego (engelberg@ucsd.edu). Mullins is at the Rady School of Management, UC San Diego (wmullins@ucsd.edu).

Figure A.1: 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.

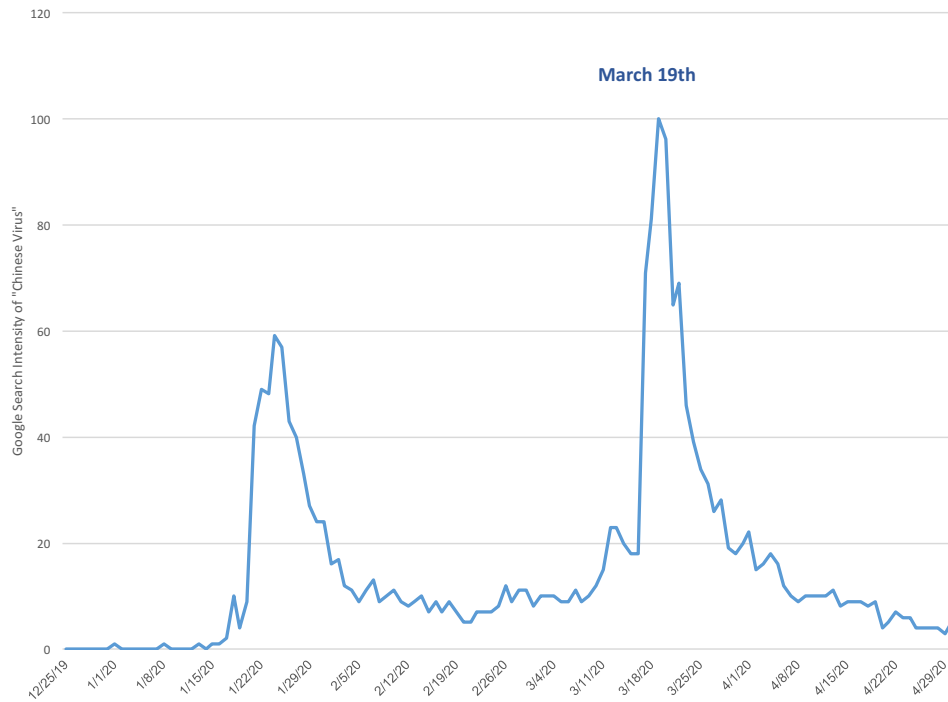


Figure A.2: Trump Tweets Mentioning “Chinese Virus”

This figure presents a screenshot from Trump Twitter Archive, with the search term “Chinese Virus.” President Trump authored 8 tweets with the term, each of which occurring near the peak of Google Search Intensity noted in Figure A.1.

8

Chinese virus

Tips ▾

@realdonaldtrump

Export ▾

Options ▾

↓

mm/dd/yyyy

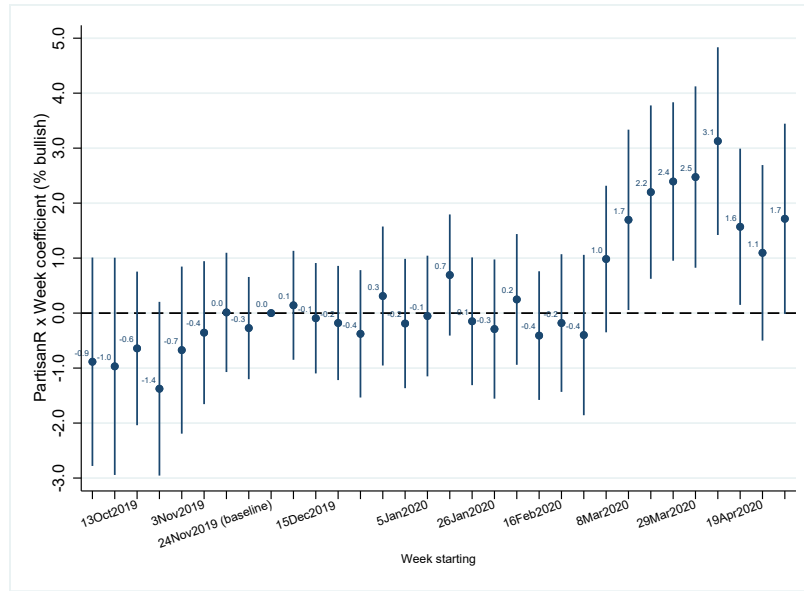
mm/dd/yyyy

| | |
|--|--|
| Mar 22, 2020 08:20:08 PM | My friend (always there when I've needed him!), Senator @RandPaul, was just tested "positive" from the Chinese Virus. That is not good! He is strong and will get better. Just spoke to him and he was in good spirits. [Twitter for iPhone] link |
| Mar 21, 2020 09:53:27 PM | CHINESE VIRUS FACT CHECK https://t.co/qJugCylvE2 [Twitter Media Studio] link |
| Mar 18, 2020 04:37:22 PM | I only signed the Defense Production Act to combat the Chinese Virus should we need to invoke it in a worst case scenario in the future. Hopefully there will be no need, but we are all in this TOGETHER! [Twitter for iPhone] link |
| Mar 18, 2020 06:46:33 AM | I always treated the Chinese Virus very seriously, and have done a very good job from the beginning, including my very early decision to close the "borders" from China - against the wishes of almost all. Many lives were saved. The Fake News new narrative is disgraceful & false! [Twitter for iPhone] link |
| Mar 18, 2020 06:12:49 AM | I will be having a news conference today to discuss very important news from the FDA concerning the Chinese Virus! [Twitter for iPhone] link |
| Mar 18, 2020 05:41:14 AM | For the people that are now out of work because of the important and necessary containment policies, for instance the shutting down of hotels, bars and restaurants, money will soon be coming to you. The onslaught of the Chinese Virus is not your fault! Will be stronger than ever! [Twitter for iPhone] link |
| Mar 17, 2020 07:22:11 AM | Cuomo wants "all states to be treated the same." But all states aren't the same. Some are being hit hard by the Chinese Virus, some are being hit practically not at all. New York is a very big "hotspot", West Virginia has, thus far, zero cases. Andrew, keep politics out of it.... [Twitter for iPhone] link |
| Mar 16, 2020 05:51:54 PM | The United States will be powerfully supporting those industries, like Airlines and others, that are particularly affected by the Chinese Virus. We will be stronger than ever before! [Twitter for iPhone] link |

Figure A.3: Partisan Republicans are More Optimistic than Other Users During COVID – Weekly Fixed Effects

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 runs from October 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 on the subset of S&P500 stocks.

(a) All Stocks



(b) S&P500 Stocks

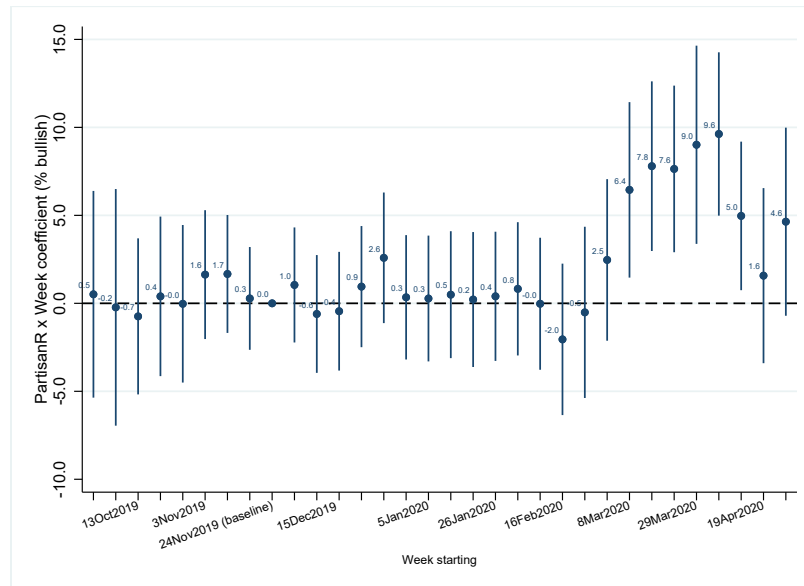


Figure A.4: Partisan Disagreement and Abnormal Trading Volume – Leads and Lags Plot

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 runs from March 2019 through April 2020. The vertical bars illustrate 95% confidence intervals with standard errors double clustered at the stock and day levels.

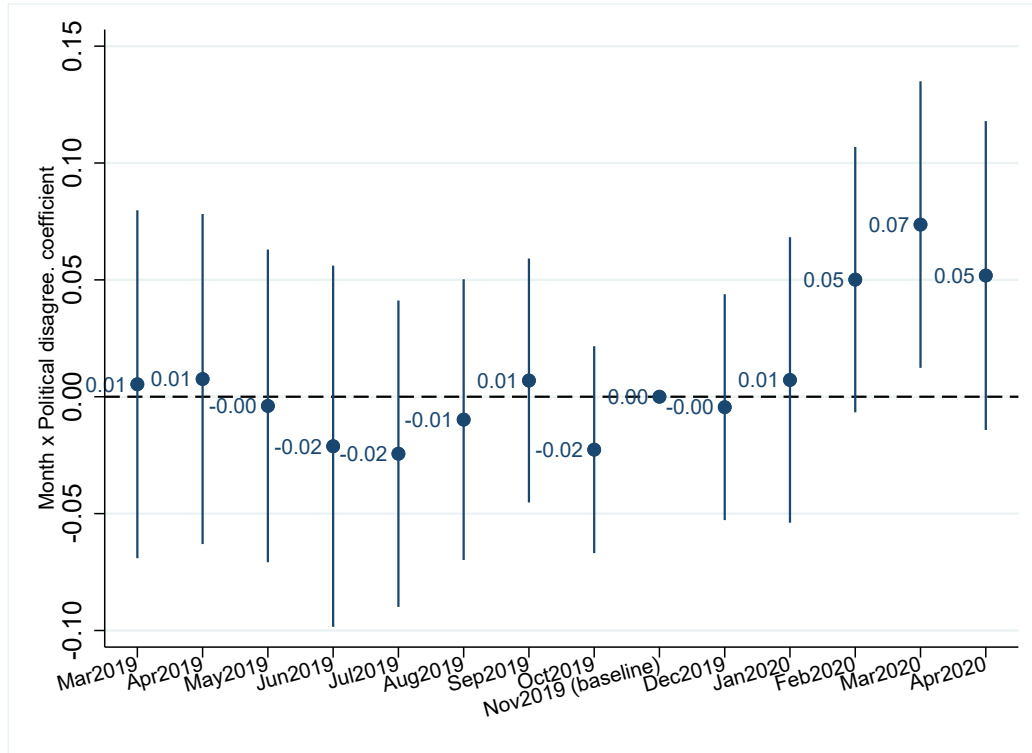


Table A.1: List of Stocks with Largest Percentage Loss (Jan 1 – Mar 23)

To give context for the partisan Republican optimism about stocks that recently lost value, 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% |