Partisan Return Gap:
The Polarized Stock Market in the Time of a Pandemic

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Abstract

Using two proxies for investors' political affiliation, we document sharp differences in stock returns between firms likely dominated by Democratic investors (blue stocks) and those dominated by Republican investors (red stocks) during the COVID pandemic. Red stocks have 20 basis points higher risk-adjusted returns than blue stocks on COVID news days (*Partisan Return Gap*). Lockdown policies, COVID cases, industry and firm fundamentals only explain at most 25% of the return gap. Polarized political beliefs about COVID, revealed through people's social distancing behaviors and their StockTwits, contribute to about 40% of the return gap beyond the fundamental channel. Our paper provides partisanship as a novel aspect in understanding abnormal stock returns during the pandemic.

Keywords: Partisanship, Stock returns, Pandemic, COVID-19, Political polarization, Political finance, Social finance

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"The coronavirus crisis once seemed to be the kind of gut-wrenching shock that would pull together a politically divided nation. Increasingly, though, it is pulling the nation apart along familiar lines."

— *Wall Street Journal*

1 Introduction

Partisanship and affective polarization have been increasing dramatically in the past decades (e.g., Gentzkow, Shapiro, and Taddy 2019; Canen, Kendall, and Trebbi 2021). Even financial regulators like the SEC exhibit strong partisanship (Engelberg, Henriksson, Manela, and Williams 2021). A growing body of research in finance and economics finds evidence that partisanship exerts a significant influence on people's expectations and beliefs (e.g., Ke 2020). Yet, the literature so far has limited knowledge about whether and how partisanship affects asset prices.

In this paper, we study whether partisanship affects stock returns during the COVID-19 pandemic. Two features render this pandemic a particularly powerful setting. First, it has been well documented that people belonging to different parties strongly disagree about every aspect of COVID, ranging from the severity of the pandemic, how to curtail it, to whether people should get the vaccine (e.g., Allcott et al. 2020; Fan, Orhun, and Turjeman 2020). The political polarization during the pandemic is unprecedented. In general, Republican is more optimistic about COVID than Democrats.[2] Second, during the first few months of the COVID pandemic, the stock market has seen a record number of large price movements triggered by COVID-related news. News about COVID cases, vaccinations, and government intervention are brought to the market on a daily basis, which have generated a significant price impact on the stock market. In short, the large and persistent political

[2] This is consistent with Pastor and Veronesi (2020), who find that Republican voters are less risk averse.

disagreement about COVID combined with a dense cluster of significant COVID news offers a rare opportunity to study the impact of partisanship on stock returns.

Ex-ante it is not clear whether partisanship will affect stock returns. On the one hand, behavioral theories suggest that investors' attention and interpretation of public information could be dependent on their private information and beliefs. To the extent that partisanship affects investors' beliefs about COVID and its economic impact, it could affect how stock prices react to COVID shocks. In particular, if investors exhibit so-called "confirmation bias" in which they search for and interpret information in a way that confirms or supports their existing beliefs (e.g., Taber and Lodge 2006; Westen et al. 2006), then stocks more affected by Republicans would react more strongly to COVID related news that is consistent with their prior beliefs and less strongly to the news not consistent with their beliefs. On the other hand, the impact on belief does not necessarily pass through to investors' decisions and stock prices. For example, Giglio, Maggiori, Stroebel, and Utkus (2021) find that the pass-through from belief to portfolio choices is positive but weak, which might dampen the effects of belief changes on equilibrium prices. Therefore, whether and how partisanship affects stock prices become an empirical question.

To study the impact of political polarization on stock markets during the pandemic, we first identify the shocks of COVID to the stock market by looking at aggregate stock market movements. Specifically, we first find days on which the S&P 500 index moves by more than 2.5%, and then define a day as with a COVID shock if the main reason for the swing is related to COVID by searching major news articles.[3]

[3] The results are robust to using other thresholds such as 2%, 3%, and 5%.

We identify the partisanship of stock investors using two proxies. First, in our main specification, we use headquarter location (county) as a proxy for the partisanship of stocks.[4] Stocks of companies headquartered in Republican-dominated counties (red counties) are defined as Republican stocks (red stocks). Democrat stocks (blue stocks) are defined in the same way. This proxy is premised on the vast empirical evidence of home bias. Investors tend to concentrate holdings in stocks to which they are geographically close (e.g., Coval and Moskowitz 1999; Grinblatt and Keloharju 2001; Huberman 2001; Hong, Kubik, and Stein 2008). The implication is that the stock prices of companies headquartered in red (blue) counties are more likely to be determined by Republican (Democratic) investors. Our second proxy captures the partisanship of nonlocal investors, which do not rely on the local bias assumption. Motivated by the finding that institutional investors are more likely to invest in firms located in counties to which they have stronger social ties (Kuchler et al. 2021), we construct a social-connection-based partisanship measure (SCP) for each county based on Republican voting shares and Facebook connection data. The higher the SCP, the more likely the focal county is socially connected to Republican voters. Therefore, the stock returns of companies with higher SCP are more likely to be affected by Republican investors.

One may concern that our measures depend on retail investors being the marginal investors. While it may be true that retail investors are more subject to behavioral biases, our measures are not necessarily anchored on retail investors' beliefs. First, regarding our first proxy of headquarter location, institutional investors exhibit a strong preference for locally headquartered firms similar to retail investors (e.g., Coval and Moskowitz 1999). Second, for our second proxy of social-connection-based partisanship, institutional investors

[4] Using headquarter as a proxy for firm's location is well-accepted in the finance literature (e.g., Pirinsky and Wang, 2006; Coval and Moskowitz, 1999). Moreover, the partisan return gap is mainly among small firms, which may not have many establishments in states outside of headquarter states (see Section 5.1).

are more likely to invest in stocks that they have stronger social ties (Kuchler et al. 2021). Third, institutional investors are well-documented to have political bias (e.g., Hong and Kostovetsky 2012). Therefore, our proxies could be reflecting political beliefs of both retail and institutional investors.[5]

Anecdotal evidence suggests that red and blue stocks react differently to COVID shocks. For example, Range Resources Corporation and Montage Resources Corporation are two Texas companies in the crude petroleum and natural gas industry. Range Resources is headquartered in Tarrant County, and Montage Resources is in Dallas County. Tarrant and Dallas are neighboring counties with similarly sized populations (about 2 million). The majority in Tarrant County voted Republican during the 2016 election, while the majority in Dallas County voted Democratic. The two companies are in the same industry, are located in adjacent counties, and have similar risk exposures to common risk factors (e.g., market, size, value).[6] However, their stock price reactions to COVID-related news are very different. The average stock return of Range is 1.37% on days with COVID shocks, while Montage's average return is -1.00%. This evidence suggests that there is a significant difference in reactions to COVID shocks between red and blue stocks.

To systematically study the effect of partisanship on stock returns, we examine all public firms in the United States. We find that red stocks earn higher risk-adjusted returns than blue stocks on days with important COVID-related news. In contrast, there is no significant difference in returns between the two groups of stocks outside of the COVID news days. The economic magnitude is large. Red stocks have about 20 basis points higher

[5] Our two proxies of partisanship of firms are different from other measures, such as top management's political contributions (e.g., Hutton, Jiang, and Kumar 2015). Unlike previous studies, this paper focuses on political beliefs of investors.

[6] Betas for the Market, SMB, and HML factors are 0.97(1.07), 1.45(1.46), 0.98(0.60), respectively for Range Resources Corporation (Montage Resources Corporation). The 3-factor alpha for Range and Montage is 2.65% and 0.15% on COVID-19 shock days.

risk-adjusted returns than blue stocks on COVID news days. We find similar results when using the social connection-based partisanship measure. We call this sharp difference the *Partisan Return Gap*.

How to explain this Partisan Return Gap? We explore two potential explanations, which are not mutually exclusive. We first examine an extensive set of variables that are related to economic and firms' fundamentals, including local demographic information, firm characteristics, lock down policies, COVID cases, firms' profitability, and industry by date fixed effects. We find that these fundamental-related variables can explain at most 25% of the partisan return gap.

The fact that the fundamental channel could only explain a small fraction of the partisan return gap prompts us to explore other potential explanations related to the behavioral biases of investors. As discussed above, when encountering COVID-related news, the confirmation bias could result in each partisan interpreting it as supporting their existing beliefs, leading to return gaps between red and blue stocks. To test this idea, we examine the effect of partisanship on stock returns on days with positive and negative COVID shocks separately. Since Republicans are generally more optimistic about COVID than Democrats, they will react more strongly to good COVID news and less strongly to bad news. As a result, red stocks are likely to experience more increases in price on good news days and less decrease in price (i.e., higher returns) on bad news days. We find that red stocks have higher risk-adjusted returns than blue stocks on good news days (e.g., vaccine news). Also, red stocks have higher risk-adjusted returns than blue stocks on bad news days. These results are consistent with the confirmation bias.

To examine the underlying mechanism of the partisan return gap, we turn to individuals' attitudes toward COVID, which are proxied by their social distancing behavior. The idea is that people's political belief may influence their attitudes toward COVID, which may, in turn, affect their reactions to the COVID news when trading stocks. Using GPS location data that tracks individuals' visits to public places, we measure people's social distancing behavior by their visits to non-essential businesses (e.g., restaurants). Relative to blue-county residents, people living in red counties engage in less social distancing in response to COVID cases and lockdown policies, manifesting their perception that the disease carries less risk. More importantly, we find that firms in counties with less social distancing behavior earn higher risk-adjusted returns on COVID news days, suggesting that polarized political beliefs about COVID are important sources of cross-sectional variation in stock returns. Further investigation shows that this channel can explain about 40% of the partisan return gap.

If the partisan return gap is rooted from people's different opinions about COVID, we would expect the return gap varies with the degree of such disagreement. To test this hypothesis, we utilize the partisan disagreement measure based on StockTwits data from Cookson, Engelberg, and Mullins (2020). Indeed, we find that the partisan return gap concentrates on days when the partisan disagreement is high, consistent with the return gap being triggered by the partisan disagreement about COVID.

Several additional results also lend support to the behavioral explanation. For example, we find the return gap is concentrated among firms that are more likely to be affected by local investors (e.g., small firms). Second, we find that the return gap is stronger for firms with low institutional ownership, which are more likely to be affected by the behavioral bias of investors. Third, presumably, people with higher income and higher education have more resources for learning about the disease so should be less biased. Indeed, we find that the gap we document is concentrated in companies headquartered in low-income and low-education counties.

Finally, to address the concern on unobservable differences between companies in red and blue counties driving our results, we run a placebo test and repeat our procedures for 2018-2019. During this earlier period, we do not observe the return gap that we documented in the main analysis. Our results are also robust to controlling for labor force telework flexibility of firms and to using alternative measures of risk-adjusted returns and partisanship.

Despite the variety of risk models and the large number of stock characteristics incorporated by our analyses, one may still be concerned about missing risk factors as a potential explanation for the partisan return gap. However, several of our results pose challenges for such an explanation. First, we find that red stocks earn higher abnormal returns than blue stocks on both good and bad news days. If, for example, the higher alpha on good news days by red stocks relative to blue stocks is due to red stocks' higher loadings on a missing risk factor which earns a positive risk premium on good COVID news day, then we would expect red stocks to earn a *lower* alpha than blue stocks on *bad* news days when the missing factor likely realized a negative risk premium. Second, we find that the return gap concentrates on days when the partisan disagreement is high. If the partisan return gap was driven by missing risk factors between blue and red stocks, then one would expect it shows up on all COVID news days, irrespective of whether there is a high or low disagreement among investors.

Our paper adds to a growing literature on how partisanship affects financial decisions and outcomes. Whereas researchers have documented partisan bias in households' assessment of future economic conditions (Gerber and Huber 2010; Mian, Sufi, and Khoshkhou 2021), evidence on actual economic behavior is mixed. Some papers argue that belief bias due to partisanship influences investors' portfolio choice and spending (e.g., Gerber and Huber 2009; Gillitzer and Prasad 2018; Meeuwis, Parker, Schoar, and Simester 2021), while other papers do not find such a connection (e.g., McGrath 2016; Mian, Sufi, and Khoshkhou 2021). Therefore, whether political beliefs matter for stock returns is still an unknown question. In a related study, Cookson, Engelberg, and Mullins (2020) find that investor's partisan disagreement, measured by their language on social media platform StockTwits, can explain a significant fraction of stock turnover during the pandemic. However, they do not examine the relationship between partisanship and stock prices. Using the COVID pandemic as a powerful setting, our paper is one of the first to show that political beliefs have an important effect on stock prices.

More generally, our paper is also related to the literature on political finance. Prior studies examine the relationship between political cycles /political uncertainty and stock returns (e.g., Santa-Clara and Valkanov, 2003; Pastor and Veronesi, 2013; Kelly, Pastor and Veronesi, 2016; Pastor and Veronesi, 2020; Chen, Da, Huang, and Wang, 2021).[7] While these studies focus on time-series evidence from the aggregate stock returns, this paper examines the relationship between political polarization and the cross-sectional of stock returns. Also, these studies focus government policies, while this paper investigates the partisanship of investors of corporations, which is an important but different perspective.

This study also speaks to the new literature on explaining the unprecedented stock market volatility in the early months of the COVID pandemic. While several papers examine the causes of the stock price movements during this period, the abnormal patterns of stock returns are not well-understood yet. Some studies link stock returns of firms to their pre-pandemic characteristics, such as cash holding and debt (Ding, Levine, Lin, and Xie 2021); financial flexibility (Ramelli and Wagner 2020; Fahlenbrach, Rageth and Stulz 2021), labor

[7] Other studies focus on the impact of political belief on corporate finance, such as corporate policies (Giuli and Kostovetsky, 2014; Hutton, Jiang, and Kumar, 2014), corporate litigation (Hutton, Jiang, and Kumar, 2015), and analyst behavior (Jiang, Kumar, and Law, 2016). Relatedly, existing literature examines the relationship between political beliefs and loan pricing (Dagostino, Gao, and Ma, 2020), housing price (Baldauf, Garlappi, and Yannelis, 2020), and investors' value proposition (Hong and Kostovetsky, 2012).

force telework flexibility (Favilukis, Lin, Sharifkhani, and Zhao 2020), and disclosed risks in 10-K filings (Davis, Hansen, and Seminario-Amez 2020). Both theoretical and empirical evidence show that plausible fluctuations of fundamentals such as economic growth, aggregate economic activities, corporate profit shares, and interest rates are unable to explain the stock market's trajectory during the COVID pandemic (Cox, Greenwald, and Ludvigson 2020; Gormsen and Koijen 2020). They argue that stock price fluctuations are mainly caused by changes in beliefs or sentiment.

However, these studies do not explain what type of sentiment or beliefs are important in explaining stock returns during the COVID pandemic. Our paper bridges the gap in the literature and shows that political beliefs are important in understanding the abnormal prices movements during this period. The partisanship aspect is novel to existing studies, and it is a first-order variable because political polarization has become one of the most important driving forces in the US.[8]

This paper is also related to Bizjak, Kalpathy, Mihov, and Ren (2021), who study the effects of CEOs' political leaning on store-level activities in the retail industries. They find there is a difference between firms' policies with republican CEOs and democratic CEOs during the COVID pandemic. Different from their paper's focus on corporate side and public health, this paper examines the asset pricing implications of political polarization. Also, our paper examines all public firms rather than just retail industry. Therefore, the implications are broader.

Our paper also contributes to the growing literature on social finance. Studies in social finance investigate how social interaction affects financial decisions (Hirshleifer 2020;

[8] While this paper focuses on stock markets, it is also related to studies on the effects of COVID pandemic on investor expectations (Giglio, Maggiori, Stroebel, and Utkus 2020), corporate bond market (Falato, Goldstein, and Hortaçsu 2021), different asset classes (Boudoukh, Liu, Moskowitz, and Richardson 2020), as well as the long-term effects of the pandemic on beliefs (Kozlowski, Veldkamp, Venkateswaran, 2020).

Han, Hirshleifer, and Walden 2020). Bailey et al. (2018) show that social interaction measured by Facebook connections can affect housing purchase decisions. Kuchler et al. (2021) show that institutional investors are more likely to invest in firms in regions to which they have stronger social connections. Our paper complements these studies by showing that political beliefs can have a significant impact on the stock prices of local firms and firms that are geographically far away but socially connected. Our finding highlights the important role of social interactions in understanding stock returns.

2 Data and Measurement

2.1 Data

Our sample includes all public companies from the CRSP/Compustat Merged Database. We restrict our sample to common share stocks listed on NYSE, Nasdaq, and AMEX and exclude companies that have no book value in the fiscal year ending in 2019 or no market value at the end of 2019. We also exclude penny stocks and firms whose headquarters are outside the United States. Our final sample consists of 3,027 firms. We focus on the sample period from January 1, 2020, to June 30, 2020, because this is the period when COVID-related events triggered large market movements.

We merge Compustat headquarter information with county-level voting history. We obtain 2016 presidential election voting results from the MIT Election Data & Science Lab.[9] We measure local partisanship with the proportion of votes for Republican and Democratic candidates in the area. A county is labeled as *red* (*blue*) if the Republican candidate received more (fewer) votes than the Democratic candidate in the county.

To measure individuals' social distancing behavior, we use anonymized foot traffic data from SafeGraph. Partnering with smartphone applications, SafeGraph obtains GPS

[9] The data is available here: https://doi.org/10.7910/DVN/NH5S2I.

location data from 45 million smartphones and aggregates it to identify customer visits to public places. There are over 6 million uniquely identified public places in the dataset, such as shops, restaurants, hotels, and airports. For each place, we observe its address, industry classification, and the number of visits each day.

To measure social connections between counties in the United States, we use the *Social Connectedness Index* developed by Bailey et al. (2018).[10] Based on anonymized friendship links of Facebook users, the county-level pairwise index captures the likelihood of residents in any two U.S. counties being Facebook friends. Because Facebook has a large user base and requires mutual consent to establish friendship links, Facebook friendships provide a good proxy for real-world social connections.

We obtain other state- and county-level variables from various sources. Daily COVID cases are from the *New York Times*. Government lockdown orders are extracted from the dataset collected by Keystone Strategy. Weekly unemployment claims are from the U.S. Department of Labor website. County demographics are from the 2012-2016 American Community Survey (ACS) and the U.S. Census Bureau. Religiosity information is from "U.S. Church Membership Data" collected by the Association of Religion Data Archives.

2.2 Measurement

To identify significant COVID-related news, we utilize the aggregate stock market movements. For example, on March 12, 2020, the U.S. government imposed a ban on travel to and from Europe, and the S&P 500 index dropped 10%. In contrast, on March 24, 2020, and March 26, 2020, the news media reported that Congress and the government were about to agree on a $2 trillion stimulus plan, and the stock market rebounded strongly by 9% and 6%. We focus on days when the S&P 500 index moves up or down by more than 2.5%,

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[10] The data is available here: https://dataforgood.fb.com/tools/social-connectedness-index/.

which is about the threshold of the top and bottom 10% of S&P 500 returns during the sample period. The results are robust to using alternative thresholds (see Section 5.3). From January 1, 2020, to June 30, 2020, there are 33 days when the stock market rose or fell by more than 2.5%. We use news articles to identify whether the main reason for each swing is COVID. Figure 1 plots some major events during the period. The complete list of the 33 days and related news articles is in the Appendix. The news on only 5 of the 33 days is not related to COVID. The remaining 28 days are driven by COVID news, and we label them *COVID Shock* days. We further define *Positive (Negative) COVID Shock* to distinguish market rises from market falls. There might be concerns that because COVID-related news occurred almost every day in 2020 the stock market swings on those 5 days might also be related to COVID. In a robustness test in Section 5.3, we also include these 5 days, and the results are similar.

To construct risk-adjusted daily returns of individual stocks, we calculate Fama-French 3-factor alpha (Fama and French 1993) from January 1, 2018, to June 30, 2020. We use other risk factor models such as CAPM, Fama-French-Carhart 4-factor, and Fama-French 5-factor in robustness tests. We also calculate *turnover* as the daily trading volume divided by total shares outstanding. To measure corporate earnings, we define *ROA* as income before extraordinary items divided by total assets. Following Novy-Marx (2013), we calculate gross *profitability* as returns on gross profits (revenues minus cost of goods sold) scaled by total assets. We then denote the year-over-year change in ROA and gross profitability as *ΔROA* and *ΔProfitability*.

To measure individuals' social distancing behavior, we calculate the demeaned change in visits to non-essential businesses compared to pre-pandemic levels. Specifically, we define non-essential services as those whose 2-digit NAICS code is 71 (Arts, Entertainment, and Recreation) or 72 (Accommodation and Food Services).[11] We sum up the total number of non-essential visits for each county on each day and calculate its 5-day moving average to adjust for weekly seasonality.[12] We then divide it by the number of visits at the beginning of 2020 to gauge the reduction in visits due to COVID. Finally, to measure the cross-sectional variation of social distancing behavior, we subtract the daily average change in visits across all companies from each observation.

To measure local economic conditions and policy responses to COVID-19, we define *new cases* as the state-level new COVID cases per 1,000 residents each day. *% Unemp* is the state-level unemployment claim rate during a week. *Lockdown* indicates whether there is a state-level "shelter-in-place," "non-essential services closure," or "closing of public venues" order in effect on a given day. We focus on the three types of lockdown orders because they have a direct impact on business operations. In addition, we define *% Female* as the percentage of women in a county and *HH Income* as the median household income over the past 12 months. We measure local religiosity as the proportion of a county's total population that attends church, using the 2010 survey conducted by the Association of Religion Data Archives (ARDA). The *total religiosity ratio (TRR)* is calculated as the number of adherents of all religious denominations divided by the total population of the county.

[11] These industries include: theaters; sport centers; museums; historical sites; zoos; amusement parks; casinos; golf courses; hotels and inns; RV parks and campgrounds; bars; restaurants; cafeterias.

[12] There are only data for trading days (Monday-Friday), so 5-day moving average removes weekly seasonality.

2.3 Summary statistics

Table 1 presents summary statistics of key variables in our main analysis. The average risk exposure (i.e., betas) to $R_m - R_f$, SMB, and HML are 0.93, 0.78, and 0.31, respectively. The average Fama-French 3-factor (FF3) alpha is 0.045%, suggesting that the Fama-French 3-factor model does a good job capturing firms' risk exposure. During the sample period, 22% of trading days are labeled as COVID Shock days, of which 10% are positive shocks and 12% are negative shocks. Out of 3,027 firms in the sample, 20% are in red counties, and the average voting share for the Republican candidate in the 2016 presidential election is 37%. Regarding COVID severity, the average number of daily new COVID cases is 0.074 per 1,000 residents. From Jan. 1, 2020 – June 30, 2020, people reduced their visits to non-essential service providers by 39%. The average unemployment claim rate is 14% at the state level, and 43% of firm-date pairs are associated with at least one of the "shelter-in-place," "non-essential services closure," or "closing of public venues" orders. For counties in our sample, the average median household income is $68K per year. The average proportion of women and proportion of residents attending church are both 51%. The average firm in the sample has a market value of $10.3 billion, a book-to-market ratio of 0.57, and institutional ownership of 54%. During 2020Q1 – 2021Q1, the average return on assets and gross profitability is -2.4% and 4.5%, a decrease of 0.8 and 1.2 percentage points from the same period in the previous year.

3 Partisan Return Gap

In this section, we document that there are striking differences in stock price reactions to COVID shocks between firms headquartered in blue counties and firms headquartered in red counties. We examine both the characteristics of firms and their stock prices during the COVID period.

3.1 Differences between red and blue firms

We first examine whether there are systematic differences in characteristics between companies headquartered in blue counties and companies headquartered in red counties. Table 2 Panel A presents a comparison of several firm characteristics. We find that blue stocks have higher market capitalization and lower book-to-market ratios. Given that the focus of this study is on stock returns, we also examine their risk exposures to the Fama-French 3 factors. We find that red stocks have significantly higher exposure to the value risk factor. Given this finding, it is important to control for risk exposure when comparing stock returns. Therefore, we use Fama-French 3-factor alphas as a measure of stock performance.

We also look at the industry distributions of these firms based on the Fama-French 12- industry classification. Table 2 Panel B shows that red stocks are concentrated in industries such as manufacturing, wholesale, retail, and some services, while blue stocks are mainly in industries such as business equipment, finance, and healthcare. Given the differences in industry distribution among these firms, we include industry-fixed effects in our regression to control for that.

3.2 Partisan return gap: main results

We now compare the behavior of stock returns for firms in blue counties and red counties. We use the abnormal return adjusted by Fama-French 3 factors, $AbnRet_{i,t}$, as the dependent variable. We estimate the following regression:

$$\begin{aligned} AbnRet_{i,t} = \alpha + \beta_1 COVID\_Shock_t + \beta_2 Red_i + \beta_3 COVID\_Shock_t \times Red_i \\ + \sum\nolimits_{j=1}^{n} \gamma_j X_{i,t}^j + \sum\nolimits_{j=1}^{n} \theta_j COVID\_Shock_t \times X_{i,t}^j + FEs + \epsilon_{i,t} \end{aligned} \quad (1)$$

where *COVID_Shock*$_t$ is a dummy variable that equals 1 if COVID-related news on day t triggered the S&P 500 index to move by more than 2.5%. *Red*$_i$ is a dummy variable that equals 1 if firm i is headquartered in a Republican county.[13] We define a county as Republican if the Republican candidate received a larger share of votes in the 2016 presidential election. Figure 2 displays the geographic distribution of red and blue counties.

Table 3 presents the results of this test. In column (1), the coefficient on *COVID_Shock* is negative and significant, suggesting that the abnormal returns for blue stocks are negative on COVID news days. Although this result may appear to be mechanical since more of these shock days are days with big drops in the stock market, these are abnormal returns adjusted for risk exposure. The variable *Red* itself is close to 0 and statistically insignificant, suggesting that on days with no COVID shocks there is no significant difference in returns between the red and blue stocks. The main variable of interest is the interaction term *COVID_Shock* × *Red*. Its coefficient is positive and significant, suggesting that the abnormal returns of red stocks are greater than those of blue stocks on days with COVID shocks.

The economic magnitude of this difference is large. For example, the coefficient on the interaction term is 0.20 in column (2), meaning that red stocks earn 0.20% higher abnormal returns than blue stocks on COVID news days. We call this return difference the *Partisan Return Gap.*

We include an extensive set of control variables. Korniotis and Kumar (2013) show that when the local economy experiences a stronger recession than the national economy,

[13] In our main specification, we use *Red* as an indicator variable instead of the percentage of Republican votes because the effect of election results on stock returns is likely to be nonlinear. Smaller counties are likely to have more unified election outcomes, with either a very high or very low percentage of Republican votes. However, local investors in smaller counties are less likely to have an impact on stock prices. Thus, the effect of Republican voters on stock prices is likely to be weaker when the vote percentage is either very high or very low. In the robustness section, however, we use the continuous percentage of Republican votes as an alternative measure of partisanship, and the results are robust.

local investors are likely to become more risk-averse and sell local stocks, which could generate lower returns on the COVID news days. We thus include state-level weekly new unemployment claims and their interaction with $COVID\_Shock_t$ as control variables. We also control for county demographics such as gender, income, and religiosity. In addition, Daniel and Titman (1997) show that firm characteristics provide additional explanatory power of returns beyond corresponding risk factors. Thus, we also include market value and book-to-market ratio in the regression. Column (2) presents the result. With this set of controls, the coefficient on $COVID\_Shock \times Red$ remains unaffected and positively significant.

One concern is that the stock underperformance of firms in blue counties may be the result of differences in industry composition. In column (3), we include firm fixed effects and Fama-French 12 industries by date fixed effects to control for industry differences. The Industry $\times$ Date fixed effects is a strong control as we are now comparing returns of companies in the same industry on the same day. Including fixed effects increases the R^2 significantly, however, the Partisan Return Gap is only slightly reduced in magnitude to 0.17% and remains statistically significant. Taken together, these findings suggest that there is a robust return difference between red and blue stocks.

So far, our definition of whether a firm is blue or red is based on its headquarters location. We also explore another setting where we do not rely on the home bias of investors. Kuchler et al. (2021) show that institutional investors are more likely to invest in firms in regions to which they have stronger social ties, as measured by the *Social Connectedness Index (SCI)* from Facebook.[14] Moreover, this effect of social proximity on investment behavior is distinct from the effect of geographic proximity. Thus, we construct another measure

[14] According to Bailey et al. (2018), SCI is a county-level measure based on Facebook friendship links. It captures the relative probability of residents in any two U.S. counties being Facebook friends. It is calculated as the number of Facebook friend pairs between two counties divided by the product of the two counties' population and then scaled up by a factor of 10.

of partisanship of investors of firms by focusing on non-local investors. Specifically, we construct Social-Connection-based Partisanship (SCP) by calculating a log weighted sum of Republican voting shares in the 2016 presidential election, where the weight is the SCI between the county of interest and other counties, as follows:

$$SCP_i = log\left(\sum_{j(j \neq i)} \left(SCI_{i,j} \times RepVote_j\right)\right)$$

To focus on nonlocal investors, we exclude own county in the calculation. Figure 3 presents the geographic distribution of the SCP measure, and it shows that SCP is correlated with our main measure of partisanship (correlation is 0.51) but also different. Using SCP, we test whether firms located in counties with strong social ties to red counties (and thus more likely to have Republican investors) tend to have different stock reactions to COVID shocks than those located in counties with strong social ties to blue counties (and thus more likely to have investors who vote Democratic). We run a regression similar to that in Equation (1) and replace *Red* with *SCP*. Table 3 Panel B shows the results of this test. The coefficient on the interaction term *COVID Shock* $\times$ *SCP* is positive and significant, suggesting that red stocks have greater abnormal returns on COVID news days than blue stocks. This result provides further evidence of the Partisan Return Gap.[15]

4 Explanations

Why do stock prices of firms headquartered in red counties behave differently from those headquartered in blue counties on COVID news days? In this section, we explore potential explanations.

[15] To conserve space, we only report the main results using the SCP measure in the paper, and report other results using SCP in the Internet Appendix.

4.1 Lockdown policies, COVID cases, and firm fundamentals

One explanation for the return gap is that blue counties are more affected by COVID in the early stages of the pandemic. For example, New York was the state with the highest number of cases in March 2020. Figure 4 shows that Democrat-dominated areas are associated with more coronavirus cases and earlier government lockdown orders. As a result, firms in blue counties are more negatively affected by COVID shocks since many of them can no longer operate for business, leading to weaker fundamentals and lower returns.[16]

To explore this channel, we augment regression equation (1) by controlling for lockdown policy and COVID cases. Table 4 columns (1) – (2) present the results. We find that COVID cases and lockdown policies indeed have a significant impact on stock returns on COVID news days. However, the coefficient on the interaction term between COVID shocks and red is not affected in any notable way, suggesting that the return gap is not driven by lockdown policies and COVID cases.

While lockdown policies and COVID cases are important, it is more direct to examine firm fundamentals. We examine this channel by looking at firm profitability.[17] We augment regression equation (1) by controlling for year-over-year changes in profitability. Table 4 columns (3) – (4) present the results. The coefficient on the interaction term remains statistically significant, suggesting that the return gap remains there after controlling for firms' fundamentals.

To further explore the fundamental channel, we compare the profitability of the red and blue stocks in the five quarters following the outbreak of COVID in the US (i.e. 2020Q1-2021Q1). If the return gap results from investors' rational expectations of different future earnings between red and blue stocks, then we should see less reduction in earnings for

[16] Prior literature shows that local economic factors can affect the stock returns of local firms (Tuzel and Zhang 2016; Jin and Li 2020).

[17] The results are similar when using ROA as a measure of firms' fundamentals.

companies located in red counties. We test this conjecture by looking at the firm's fundamentals, measured by changes in profitability and ROA. Table 5 presents the results. The coefficient on *Red* is insignificant and close to zero, suggesting that firms in red counties do not have stronger fundamentals than firms in blue counties.

Overall, these results suggest that there is weak evidence that the return gap is driven by lockdown policies, COVID cases, or firm fundamentals. Even if we count the effect from Industry $\times$ Date fixed effects in Table 3 as part of the fundamental channel since that may capture the effect of COVID on different industries, it only explains at most 25% ((0.2-0.15)/0.2) of the Partisan Return Gap.

4.2 Behavioral channel: polarized political beliefs

Another potential explanation for the return gap is related to the behavioral channel. Prior literature finds that people display a confirmation bias in that they tend to search for and interpret information in a way that confirms or supports their existing beliefs, resulting in belief polarization (e.g., Taber and Lodge 2006; Westen et al. 2006). The effect is particularly strong when people encounter ambiguous evidence. As a brand-new disease, COVID generated a lot of news that was subject to interpretation. People who are presented with ambiguous or conflicting COVID news reports may choose to believe the reports that support their existing attitudes, widening rather than narrowing the disagreement between themselves and others.

This confirmation bias could lead to more polarized stock prices between red and blue stocks on COVID news days because investors tend to believe information that supports their already established opinions and discount information that disagrees. It is widely reported that residents in Republican areas are, on average, more optimistic about COVID than Democrats are. Faia et al. (2021) find that individuals revise their beliefs more after reading the article more consistent with their prior beliefs about the severity of the impact of COVID on health and economic outcomes. Therefore, Republicans will likely react more (less) strongly to good (bad) COVID news than Democrats. As a result, red stocks are likely to have higher returns on both good COVID news days and bad news days.

To test this hypothesis, we examine positive and negative COVID shocks separately. Specifically, we run a regression similar to that in Equation (1) but with two interaction terms: *Positive COVID Shock* $\times$ *Red* and *Negative COVID Shock* $\times$ *Red*. Table 6 presents the result. The coefficient on *Positive COVID Shock* $\times$ *Red* is positive and significant for all specifications, suggesting that firms in red counties experience significantly higher abnormal returns on days with good COVID news. The coefficient on *Negative COVID Shock* $\times$ *Red* is also positive and significant, suggesting that red stocks experience less price decrease (i.e., higher returns) with bad COVID-related news. The results are consistent with the confirmation bias. Moreover, the positive coefficients on both good and bad news days make it less likely that missing risk factors are driving the return gap. If the higher alpha on good news days by red stocks relative to blue stocks is due to red stocks' higher loadings on a missing risk factor, then the same effect should generate a lower alpha for red stocks on bad news days.

To provide direct evidence on the behavioral channel, we turn to individuals' attitudes toward COVID, which are measured by their social distancing behavior. The idea is that people's political belief may influence their attitudes toward COVID, which may, in turn, affect their reactions to the COVID news. This could serve as an underlying mechanism for the partisan return gap. To test this idea, we first check whether Republicans are less nervous about COVID by examining the difference in their social distancing behavior. To measure individual social distancing behavior, we focus on visits to non-essential businesses, such as bars, restaurants, and movie theaters. Compared to essential business, visits to non-essential business are more likely to reflect individuals' opinions about COVID, as people could choose not to visit these places if they are nervous about COVID.

To understand the relation between partisanship and social distancing behavior, we regress individuals' social distancing behavior on COVID cases (or lockdown orders) and their interaction with *Red*. We measure social distancing behavior ($SDB_{i,t}$) as the demeaned change in non-essential visits on day t since the beginning of the year in the county where firm i is located. Table IA1 in the Internet Appendix presents the results of this test. The interaction term between COVID cases (or lockdown) and *Red* is positive and significant, which suggests that residents of red counties engage in less social distancing behavior in response to COVID cases and lockdown policies, manifesting their lower risk perception about the disease. This is consistent with the findings of Barrios and Hochberg (2020). The result is robust to the inclusion of control variables and county-level fixed effects.

More importantly, we analyze the relationship between social distancing behavior and local firms' stock returns. We run a regression similar to that in Equation (1), but we replace *Red* with the social distancing behavior measure (SDB):

$$\begin{aligned} AbnRet_{i,t} = \alpha + \beta_1 COVID\_Shock_t + \beta_2 SDB_{i,t} + \beta_3 COVID\_Shock_t \times SDB_{i,t} \\ + \sum\nolimits_{j=1}^{n} \gamma_j X_{i,t}^{j} + \sum\nolimits_{j=1}^{n} \theta_j COVID\_Shock_t \times X_{i,t}^{j} + FEs + \epsilon_{i,t} \end{aligned} \tag{2}$$

We exclude companies operating in non-essential service industries (NAICS code = 71 or 72) as the non-essential visits may affect the stock returns of these companies through a fundamental channel. Table 7 Panel A presents the result. The coefficient on *COVID Shock* $\times$ *Social Distancing Behavior* is positive and significant across all specifications, suggesting that firms located in counties with less social distancing behavior earn higher risk-adjusted returns on COVID news days. Taken together, the results are consistent with that red-county residents perceive fewer health hazards about COVID. Their more optimistic attitude about COVID may lead to a higher forecast of the future cash flows or lower required risk premium, contributing to higher returns of red stocks on COVID-news days.

Do people's polarized beliefs about COVID contribute to the partisan return gap? We examine how much of the return gap can be explained by people's political beliefs measured by their social distancing behavior. We augment the regression equation (1) by adding *Social Distancing Behavior* (*SDB*) and *COVID Shock* $\times$ *SDB.* Table 7 Panel B presents the result. Column (1) shows that the coefficient on the interaction term *COVID Shock* $\times$ *Red* is 0.11. To make it comparable to our baseline results, we rerun the same regression in Table 3 with a sample excluding companies operating in non-essential service industries and report the results in columns (3)-(4). The coefficient on *COVID Shock* $\times$ *Red* in column (1) is 61% of that coefficient in column (3). This suggests that about 40% of the return gap is likely due to people's different political beliefs in red counties compared to blue counties. Column (2) and (4) controls for fundamental variables and fixed effect. Comparing the coefficient on *COVID Shock* $\times$ *Red* in column (2) with that in column (4), one can see that the coefficient on *COVID Shock* $\times$ *Red* is reduced from 0.14 to 0.08 after including *COVID Shock* $\times$ *SDB* and becomes statistically insignificant. This again suggests that about 40% of the return gap can be independently explained by people's disagreement about COVID. Taken together, the results provide evidence that partisanship plays a first order role in driving stock prices during the pandemic.

To provide further evidence that the partisan return gap is due to investors' different political opinions, we examine how the return gap varies with partisan disagreement between Republican StockTwits users and others during our sample period. We use the daily partisan disagreement data from Cookson, Engelberg, and Mullins (2020). Their paper finds that the beliefs of partisan Republicans about equities remain relatively unfazed during the COVID pandemic, while other users become considerably more pessimistic. They call this difference partisan disagreement. We define a day as a high (low) disagreement day if the StockTwits partisan disagreement is above (below) the median level. Table 8 shows that the partisan return gap concentrates on days when the partisan disagreement is high. These results are consistent with the behavioral explanation that differences in political beliefs affect stock returns.

Taken together, the results in this section suggest that while firms' fundamentals can explain a fraction of the partisan return gap, a larger fraction is likely driven by differences in political beliefs and confirmation bias.

5 Additional Results and Robustness

We present additional results in this section. Also, we show that our findings are robust to various alternative specifications.

5.1 Additional evidence related to the behavioral channel

To further explore the behavioral channel, we conduct several subsample analyses. First, we look at firms that are more likely to be affected by local investors. In particular, we look at small firms, which are less widely known and hence more likely to be held by local investors. Table 9 Panel A presents the results on firm size. We indeed find that the effect is concentrated among small firms. In addition, non-S&P 500 firms are more likely to be affected by local investors. Table 9 Panel B shows that the partisan return gap is mainly concentrated among non-S&P 500 firms.

Second, while retail investors are more likely to over-react or under-react to COVID news, institutional investors are more professional and less likely to be affected by behavioral bias. Thus, we expect the return gap to be more pronounced between firms that are traded more by retail investors. Table 10 Panel A shows the result of this test. Indeed, the gap is mainly concentrated among firms with low institutional ownership.

Third, if the return gap is due to behavioral bias, the mispricing should be stronger for stocks with severer limits to arbitrage such as higher transaction costs. We examine firms with different levels of transaction cost, as measured by stock turnover. Table 10 Panel B shows that the partisan return gap is concentrated in firms with low turnover.

Finally, we examine how the partisan return gap varies by income and education levels. Presumably, people with higher incomes and more education have access to more resources for learning about the disease and so should be less biased. In Table 11 Panels A and B, we examine the partisan return gap for high- and low-income and high- and low-education counties. We find that the effects are concentrated in companies headquartered in low-income and low-education counties. The stronger partisan return gap for low-income counties is particularly interesting yet concerning. The result suggests that low-income investors are more susceptible to behavioral biases in their trading, potentially leading to more trading losses and higher income inequality.

5.2 Placebo test

There may be a concern that our results are driven by unobservable differences between companies in red and blue counties, and that these differences have nothing to do with attitudes toward COVID. For example, Miller (1977) argues that differences of opinion and short sale constraints could lead to higher stock prices. If there is a larger disagreement among investors in red counties than in blue counties, we would observe higher returns for stocks headquartered in red counties on news days. In this case, our result should hold on to any big market movement day, regardless of the trigger. To address this concern, we run a placebo test and repeat our procedure for 2018-2019. We are able to identify 13 days on which the market moved by more than 2.5%. Table 12 presents the result. The coefficient on the interaction term is very close to zero and not significant across all specifications. Thus, firms located in red counties do not earn higher risk-adjusted returns than firms in blue counties on stock market jump days. During this earlier period, we do not observe the performance gap that we document in the main regression.

5.3 Robustness

We conduct several robustness tests. First, we consider alternative measures of abnormal returns. In the main specification, we use the Fama-French 3-factor model as the benchmark. Alternatively, we adjust daily returns with the Capital Asset Pricing Model, Carhart 4-factor model (Carhart 1997), and Fama-French 5-factor model (Fama and French 2015). As Table 13 Panel A shows, our results are robust to using these three models.

Next, we consider alternative thresholds for identifying COVID shocks. In the main analysis, we identify COVID shocks by using days on which (1) the market fluctuates by more than 2.5% and (2) the movement is triggered by news related to COVID. To alleviate the concern that our attribution of the trigger may not be comprehensive, since there is news about COVID almost every day, we include all 33 days on which the market fluctuates by more than 2.5%, regardless of the reason. As column (1) in Table 13 Panel B shows, our results continue to hold. To ease the concern that our result is subject to the use of a 2.5% threshold, we also consider days on which the S&P 500 index moves by more than 2%, 3%, and 5%. There are 38, 26, and 10 trading days identified, respectively, for these thresholds. Table 13 Panel B columns (2) – (4) present the result. The coefficient on the interaction term is positive and significant across all specifications.

Also, we consider alternative measures of partisanship. Table 13 Panel C shows that the result is robust if we use the percentage of Republican votes as a measure of partisanship. In our main analysis, we divide companies into two groups based on whether they are located in a red county. Investors in the same state but from different counties could also be considered local investors. Thus, in Table 13 Panel C, we show that our results are similar if we measure partisanship at the state level. In addition, one might be concerned that our results are driven by the finance and utility industries. In column (3), we should that our results continue to hold if we exclude these two industries from our sample.

Moreover, partisanship could also be correlated with firms' opening policies which may affect firms' cash flows. For example, retail firms with Republican-leaning CEOs experience a relative increase in store visits compared to firms with Democratic-leaning CEOs during the COVID pandemic (Bizjak, Kalpathy, Mihov, and Ren 2020). While it is possible that firms located in red counties have more Republican-leaning CEOs, this is unlikely to drive our results because retail firms are a small fraction of our sample. Nevertheless, we exclude the sample of the retail industry and find that the remaining sample continues to exhibit a partisan return gap (Panel C column 4).

One may concern that some COVID shocks we identified are associated with other interpretations or confounding announcements. For example, investors may believe that the Trump administration would favor business in Republican counties with Federal aid or early access to vaccines. To examine this issue, in Table IA2 column 1, we exclude shocks related to government policy and our results are mostly unaffected. Also, some companies may happen to announce their earnings on the same day as COVID news days and investors may respond to firm-specific news as opposed to economy-wide COVID news. To address this concern, we exclude observations with earnings announcements on COVID news days (Table IA2 column 2) and the results are robust. In another test, we also include observations with earnings announcements from day t-1 to day t+1 and the results are robust (Table IA2 column 3). We also control for analyst coverage and analyst forecasts as they may possess forward-looking information about firms. Table IA3 shows that the partisan return gap is robust to controlling for these two variables.

Finally, we control for workforce flexibility. Some industries are more suitable for working from home than other industries. For example, technology industries (likely in blue counties) are more likely to adapt to work from home during the pandemic than manufacturing industries (likely in red counties). We use the labor force telework flexibility (LFTF) measure in Favilukis, Lin, Sharifkhani, and Zhao (2020) and include it as an additional control variable to our main regression. Table IA4 in Internet Appendix shows that the return gap remains economically and statistically significant after controlling for workforce flexibility.

6 Conclusion

This paper studies the impact of political polarization on the stock market during the COVID pandemic. We document sharp differences in stock price responses to COVID-related news between public firms headquartered in blue counties and those in red counties. Red stocks have significantly higher risk-adjusted returns than blue stocks on days with important COVID-related news.

We examine potential explanations for this partisan return gap. Using an extensive set of variables to measure fundamentals, we find fundamental variables can only explain at most 25% of the partisan return gap. The majority of the return gap is likely due to the behavioral explanation. In particular, we find that confirmation bias where investors tend to believe information that supports their already established opinions and discount information that disagrees may explain the return gap. We find that red stocks have higher returns on both good and bad COVID news days. Using people's social distancing behavior as a measure of their political beliefs, we show that stocks in counties where people engage in less social distancing behavior have higher returns on COVID news days. Moreover, we also find that the return gap concentrates on days with high partisan disagreement measured by investor beliefs from StockTwits.

The findings in this paper enhance our understanding of the impacts of political polarization in the United States. Political polarization affects events not just in the political domain, but also in the economic domain. Using COVID as a powerful setting, our findings suggest that the consequences of the politicization of this public health issue go beyond residents' health. It could also have significant implications for their financial welfare.

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Appendix A. Variable definition

Variable	Definition
Panel A: variables related to daily stock performance	
Raw return	Daily stock returns winsorized at the top/bottom 1% on COVID shock days.
Excess return	Raw returns in excess of daily risk-free rate.
FF3 α	Daily excess returns adjusted by Fama-French 3 factors (R_M–R_f, SMB, HML). Factor loadings are estimated using daily returns from Jan. 1, 2018, to June 30, 2020.
CAPM α	Daily excess returns adjusted by CAPM. Market beta is estimated using daily returns from Jan. 1, 2018, to June 30, 2020.
Carhart4 α	Daily excess returns adjusted by Carhart 4 factors (R_M–R_f, SMB, HML, MOM). Factor loadings are estimated using daily returns from Jan. 1, 2018, to June 30, 2020.
FF5 α	Daily excess returns adjusted by Fama-French 5 factors (R_M–R_f, SMB, HML, RMW, CMA). Factor loadings are estimated using daily returns from Jan. 1, 2018, to June 30, 2020.
Turnover	Daily trading volume divided by total shares outstanding.
Panel B: variables related to COVID-19 shocks	
COVID Shock	A dummy variable that equals 1 if news related to COVID-19 triggers the S&P 500 index to move by more than 2.5% on a day.
Positive COVID Shock	A dummy variable that equals 1 if news related to COVID-19 triggers the S&P 500 index to rise by more than 2.5% on a day.
Negative COVID Shock	A dummy variable that equals 1 if news related to COVID-19 triggers S&P 500 index to drop by more than 2.5% on a day.
Panel C: variables related to partisanship	
Red	A dummy that equals 1 if a firm is headquartered in a Republican county where the Republican candidate received more votes in the 2016 presidential election.
Red (state)	A dummy that equals 1 if a firm is headquartered in a Republican state where the Republican candidate received more votes in the 2016 presidential election.
Rep Vote (county)	County-level share of votes to the Republican candidate in the 2016 presidential election.
Social Connectedness Index	The number of Facebook friend pairs between two counties divided by the product of the two counties' populations and then scaled up by 10^{12}. It measures the relative probability of people in two counties being Facebook friends.
Social-Connection-based Partisanship (SCP)	The logarithm of a weighted sum of the Republican voting shares in the 2016 presidential election, where the weight is the Social Connectedness Index between the county of interest and other counties based on Facebook friendship links (excluding own county).

(Appendix A continued)

Panel D: local variables	
Social Distancing Behavior (SDB)	Social distancing behavior is measured as the demeaned change in non-essential visits compared to the beginning of 2020.[1] We first replace raw visits with its 5-day moving average to eliminate weekly seasonality: $$\Delta visits_{i,t} = \frac{(\sum_{\tau=t-2}^{t+2} visits_{i,\tau})/5}{(\sum_{v=1}^{5} visits_{i,v})/5} - 1$$ We then demean by subtracting the daily average Δvisits from each observation: $$SDB = \Delta Visits_{i,t} - \overline{\Delta Visits_t}$$
New Cases	The number of new COVID-19 cases per 1,000 residents in a state on a day.
Unemp	State-level new unemployment claim rate in a week.
Lockdown	A dummy that equals 1 if there's a state-level "shelter-in-place," "non-essential services closure," or "closing of public venues" order in effect on a day.
% Female	The percentage of female in a county's total population.
HH Income	The median household income in thousands of U.S. dollars in the past 12 months.
Total Religiosity Ratio (TRR)	The proportion of a county's total population that attends church. It is calculated as the number of adherents of 217 religious denominations divided by the total population of the county using survey results from the Association of Religion Data Archives.
Panel E: variables related to firm characteristics	
ME ($ million)	The market value of a firm in millions of dollars on December 31, 2019.
B/M	The book-to-market ratio, where *BE* is the book value in millions of dollars for the fiscal year ending in 2019.
S&P 500	A dummy variable that equals 1 if a stock is a constituent of S&P 500 index on December 31, 2019.
Institutional Ownership	The shares of stocks held by institutional investors divided by total shares outstanding as of December 31, 2019.
Past 12-month return	The cumulative stock return for the 12 months prior to the end of a quarter.
ROA	Income before extraordinary items (Compustat item: IBQ) divided by total assets (Compustat item: ATQ).
ΔROA	The year-over-year change in ROA ($ROA_t - ROA_{t-4}$).
Profitability	Returns on gross profits (revenues minus cost of goods sold) scaled by assets (Compustat item: (REVTQ – COGSQ)/ ATQ).
ΔProfitability	The year-over-year change in profitability ($Profitability_t - Profitability_{t-4}$).

[1] Visits are measured using smartphone location patterns. Non-essential services are defined as places whose 2-digit NAICS code is 71 (Arts, Entertainment, and Recreation) or 72 (Accommodation and Food Services). Specifically, they are: theaters; sport centers; museums; historical sites; zoos; amusement parks; casinos; golf courses; hotels and inns; RV parks and campgrounds; bars; restaurants; cafeterias.

Appendix B. List of days with large market movements

This appendix lists days on which the S&P 500 index moves by more than 2.5% between January 1, 2020, and June 30, 2020. We also summarize the explanation provided by mainstream newspapers, whether the explanation is COVID-19 related or not, and the link to related media reports.

Date	Ret.	Explanation	COVID related?	Media Coverage
2/24/20	-3.35%	Surge of cases outside China; fear of global impact of coronavirus.	Yes	WSJ: Dow Industrials Close 1,000 Points Lower as Coronavirus Cases Mount
2/25/20	-3.03%	Health officials warned that coronavirus will likely spread in the U.S.	Yes	abcNEWS: Dow Jones plunges for 2nd straight day on coronavirus fears
2/27/20	-4.42%	Confirmation of the first U.S. community spread case; growing fear that the coronavirus outbreak could cause a recession.	Yes	NYT: Coronavirus Fears Drive Stocks Down for 6th Day and Into Correction
3/2/20	4.60%	Investors' hope that central banks will lower interest rates to boost the market.	Yes	WSJ: Dow Industrials Rally 5.1% on Central-Bank Stimulus Hopes
3/3/20	-2.81%	FED cut rate by 50bp, signaling the U.S. economy could be in serious trouble because of the virus outbreak.	Yes	CNNbusiness: Dow drops nearly 800 points after the Fed's surprising news about the economy
3/4/20	4.22%	The strong Super Tuesday performance by Joe Biden boosted the market. Health care stocks led the gains.	No	NYT: Stocks Surge as Biden Leads Super Tuesday Results
3/5/20	-3.39%	California and Washington declared state of emergencies.	Yes	FOXbusiness: Dow falls nearly 1,000 points as coronavirus whipsaws markets
3/9/20	-7.60%	Oil price plummeted amid price war between Saudi Arabia and Russia and collapsed demand due to coronavirus.	Yes	FOXbusiness: Dow plunges over 2,000 points, oil collapses amid price war and coronavirus
3/10/20	4.94%	Trump propose economic relief proposals, including a payroll tax cut and loans for small businesses.	Yes	abcNEWS: Dow spikes more than 1,000 points on hopes of coronavirus economic relief
3/11/20	-4.89%	World Health Organization declares global pandemic.	Yes	WSJ: Dow Jones Industrial Average’s 11-Year Bull Run Ends
3/12/20	-9.51%	Trump declares travel ban on Europe; NBA suspended its season; colleges suspended in-person classes.	Yes	WSJ: Stocks Plunge 10% in Dow’s Worst Day Since 1987
3/13/20	9.29%	Trump declares national emergency; Pelosi says House will pass a relief bill.	Yes	NYT: Stocks Rally as Trump and Business Leaders Pledge Support

(Appendix B. continued)

Date	Ret.	Explanation	COVID related?	Media Coverage
3/16/20	-11.98%	FED cuts rate by 100bp and plans to buy $700 billion in bonds to support economy.	Yes	WSJ: The Day Coronavirus Nearly Broke the Financial Markets
3/17/20	6.00%	Fed plans to launch commercial paper funding facility; Trump seeks $1 trillion stimulus to fight COVID.	Yes	WSJ: Stocks Rise Sharply in Volatile Trading
3/18/20	-5.18%	Trump announced U.S. and Canada close border to non-essential traffic.	Yes	CBSNews: Dow closes below 20,000, wiping out nearly all the gains of Trump's presidency
3/20/20	-4.34%	Fresh measures to contain the coronavirus pandemic spooked investors; Andrew Cuomo ordered the New York state's workforce to stay home.	Yes	WSJ: Stocks Wrap Up Tough Week With Another Fall
3/23/20	-2.93%	The Senate failed for a second time to vote through the coronavirus economic relief package; Fed to extend loans and purchase government debt.	Yes	WSJ: U.S. Stocks Drop Despite Fed's Latest Stimulus Move
3/24/20	9.38%	Congress and the White House near a deal on the stimulus package after late-night negotiations.	Yes	WSJ: Dow Soars More Than 11% In Biggest One-Day Jump Since 1933
3/26/20	6.24%	Senate approves $2.2 trillion coronavirus bill.	Yes	WSJ: Dow Rallies 6.4% After Stimulus Vote
3/27/20	-3.37%	Stocks pulled back after a furious three-day rally.	No	WSJ: Stocks Drop, But Finish the Week With Big Gains
3/30/20	3.35%	Trump extended the timeline for social distancing guidelines to April 30, which many believe will reduce economic damage in the long run.	Yes	CNBC: Dow drops 400 points as stocks close out their worst first quarter ever
4/1/20	-4.41%	The White House warned that the U.S. could face as many as 240,000 deaths; Trump asking Americans to brace for an unprecedented crisis in the days ahead.	Yes	FOXbusiness: Stocks stumble as US coronavirus cases top 200,000
4/6/20	7.03%	Slower case growth in NY and lower death rate in Europe indicate progress in the fight against coronavirus.	Yes	WSJ: Dow Industrials Surge About 1,600 Points at Start of Challenging Week
4/8/20	3.41%	Hospitalizations and intensive care admissions slow down in NY; declining new coronavirus infections in Italy.	Yes	WSJ: Stocks Close Higher After Bout of Volatility

(Appendix B. continued)

Date	Ret.	Explanation	COVID related?	Media Coverage
4/14/20	3.06%	Concerns over the coronavirus ease and early-stage plans of re-opening some pockets of the economy take shape.	Yes	FOXbusiness: Dow jumps 558+ points, Nasdaq exits bear market as coronavirus concerns ease
4/17/20	2.68%	Trump told governors they could begin reopening businesses; Boeing planned to bring 27k employees back to work; Gilead Sciences made breakthrough on remdesivir.	Yes	NYT: Stocks Rally After Talk of Reopening Economy
4/21/20	-3.07%	Oil price plummeted as a historic selloff pushed West Texas Intermediate crude oil May contract to negative.	No	FOXbusiness: Dow tumbles 631 points as oil selloff deepens
4/29/20	2.66%	FED promised to use more tools to aid the economic recovery; Gilead Sciences got positive results evaluating remdesivir on coronavirus patients.	Yes	FOXbusiness: Stocks surge on Gilead's coronavirus drug and Fed's pledge to keep rates near zero
5/1/20	-2.81%	Tech giants' revenues fall below expectations.	No	WSJ: Tech Giants Pull Stocks Lower as Dow Falls More Than 600 Points
5/18/20	3.15%	Drugmaker Moderna announced progress toward a COVID-19 vaccine; Fed pledge for further stimulus; lockdowns continued to ease nationwide.	Yes	FOXbusiness: Dow surges over 900 points amid coronavirus vaccine progress as lockdowns ease
6/5/20	2.62%	The unemployment rate unexpectedly fell to 13%, after estimates that it could hit 20%.	No	WSJ: Stocks Close Sharply Higher on Surprisingly Upbeat Jobs Report
6/11/20	-5.89%	COVID-19 infections resurge as more states reopened; Fed warned of a slower economic recovery.	Yes	WSJ: U.S. Stocks End Sharply Lower as Coronavirus Worries Return
6/24/20	-2.59%	New coronavirus cases have surged in several states.	Yes	WSJ: Stocks Fall as Coronavirus Infections Surge

Figure 1. Major events that triggered large market movements

This figure plots the historical price of S&P 500 index and major events that triggered large market movements between January 1, 2020 and June 30, 2020.

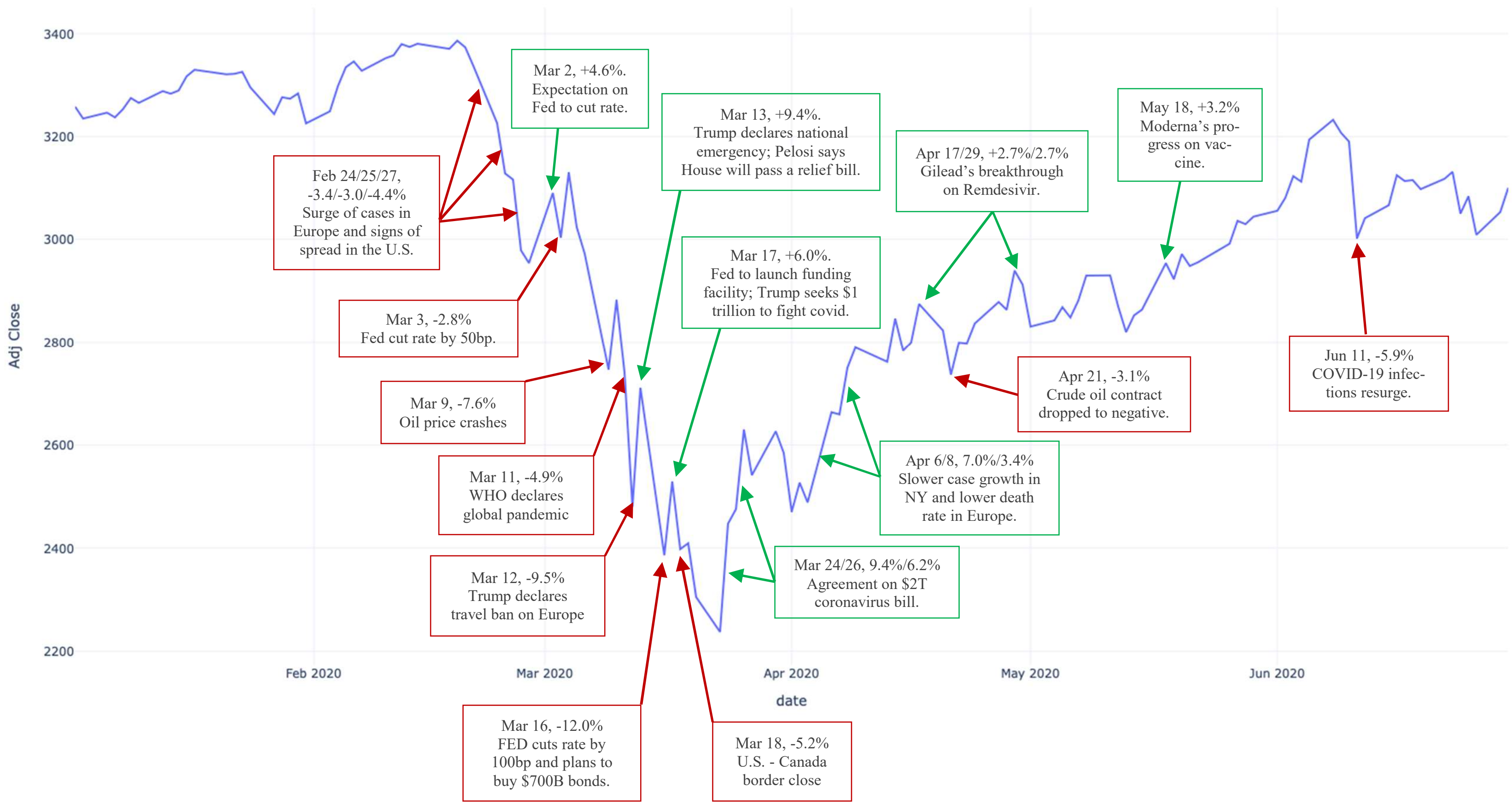


Figure 2. County-level Partisanship based on 2016 Presidential Election Result

This figure plots the share of votes received by the Republican and Democrat candidates in the 2016 presidential election. Red indicates more votes for the Republican. Blue indicates more votes for the Democrat. The darker the color, the greater the difference in votes between the two.

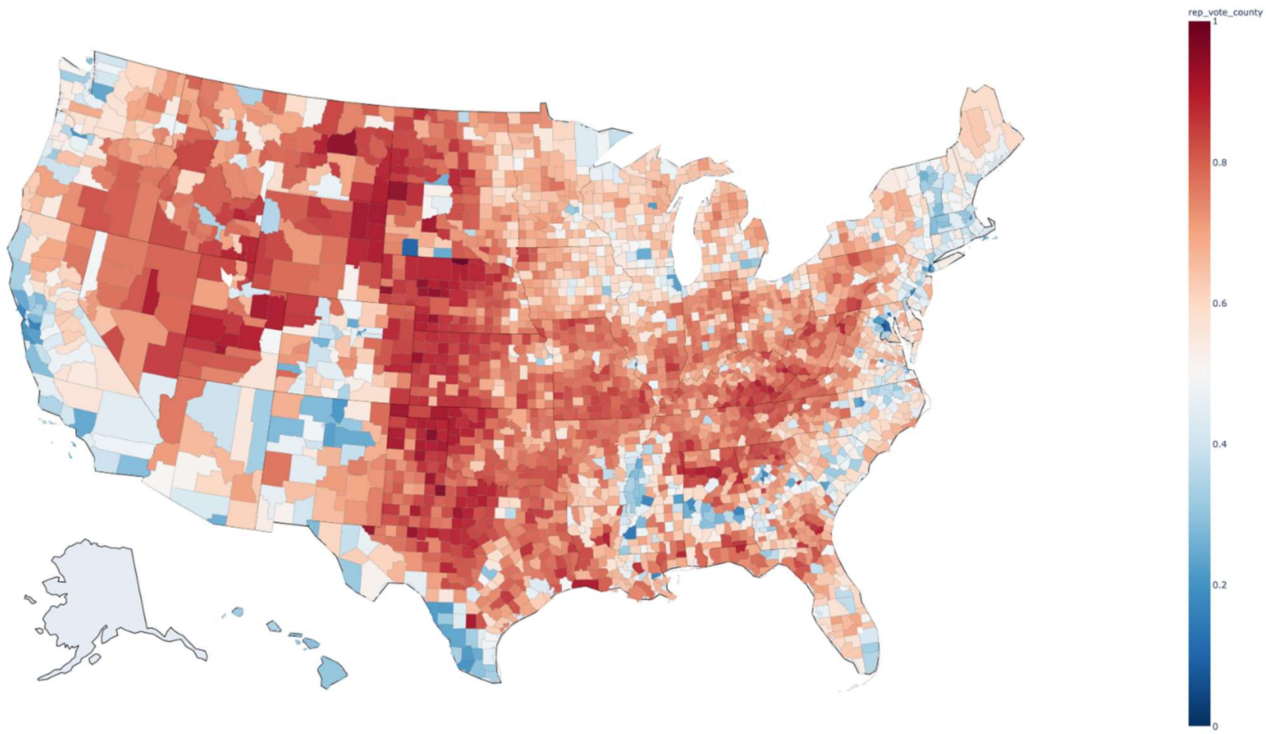


Figure 3. Social-Connection-based Partisanship

This figure plots the *Social-Connection-based Partisanship (SCP)* measure across U.S. counties. *SCP* is the logarithm of a weighted sum of the share of votes to the Republican Party in the 2016 presidential election, where the weight is the *Social Connectedness Index* between the county of interest and other counties (excluding own county). The *Social Connectedness Index* measures the relative probability of people living in two counties being Facebook friends. It is calculated as the number of Facebook friend pairs between two counties divided by the product of the two counties' populations. It is then scaled up by a factor of 10^{12} to become an integer. A county with a high *SCP* means that it is more socially connected to voters of the Republican Party. Thus, high-SCP counties are colored red, and low-SCP areas are colored blue.

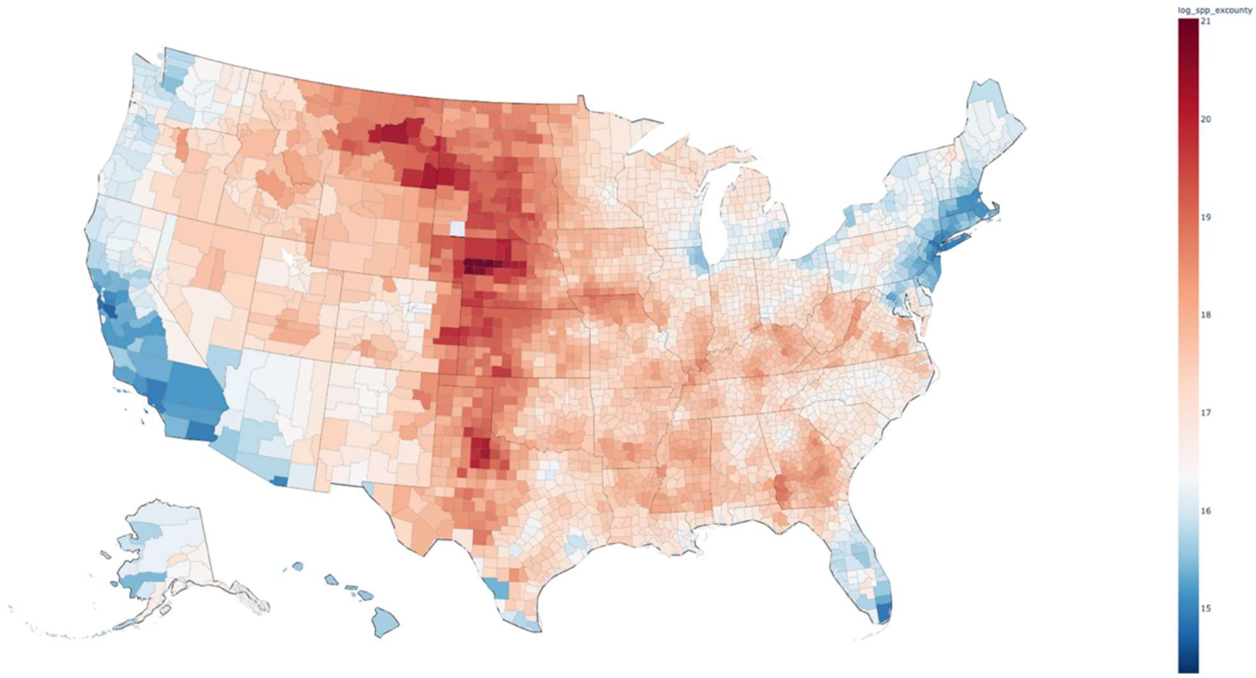
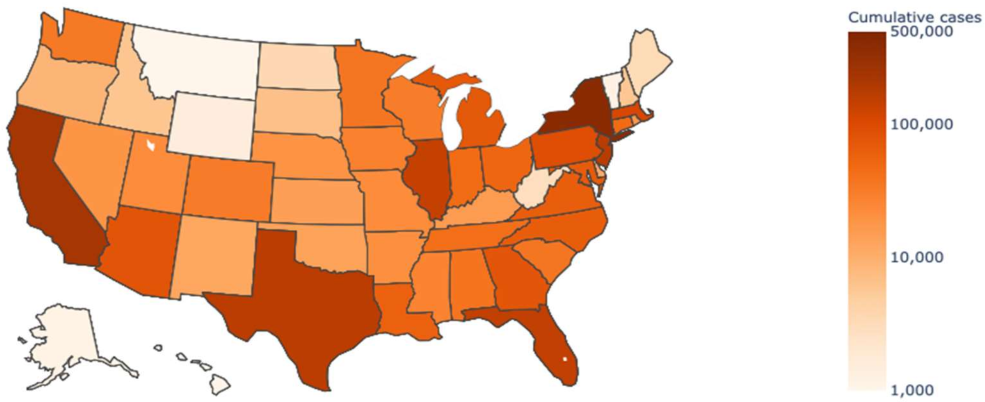


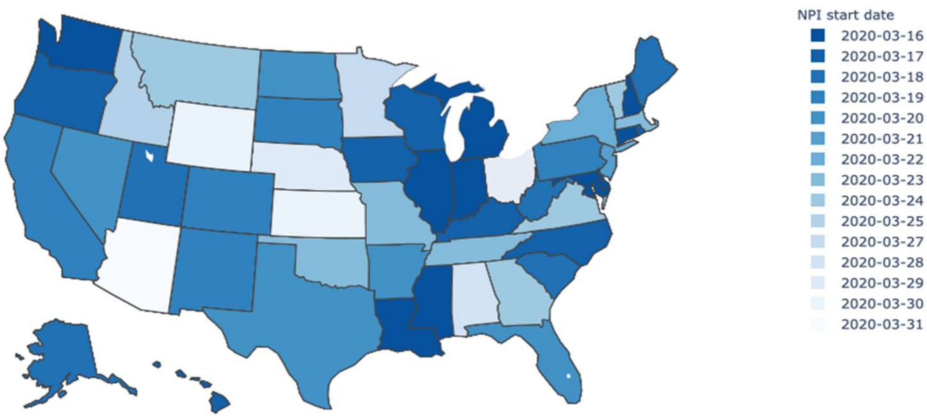
Figure 4. COVID-19 cases, government orders, and unemployment across states

This figure plots the geographic distribution of COVID-19 cases, government lockdown orders, and the unemployment rate across the United States. Panel A shows the cumulative COVID-19 cases; Panel B presents the earliest start date of three types of government orders: non-essential business closure, closing of public venues, and shelter-in-place; Panel C plots the unemployment claim rates.

Panel A: Cumulative COVID-19 cases (as of June 30, 2020)



Panel B: Government NPI start date



Panel C: Unemployment claim rate (as of July 4, 2020)

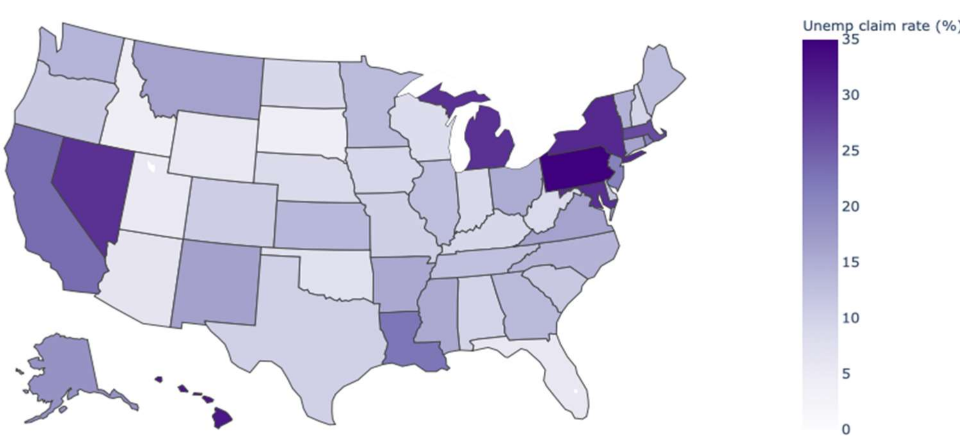


Table 1. Summary statistics

This table presents summary statistics at the firm-date level from January 1, 2020, to June 30, 2020. We restrict our sample to stocks listed on Nasdaq, NYSE and Amex. We exclude companies that have no book value in the fiscal year ending in 2019, no market value at the end of 2019, or penny stocks whose price falls below $1. Panel A shows variables related to stock performances. Raw return measures daily stock returns winsorized at the top/bottom 1% on COVID shock days. Excess return equals raw return minus risk-free rate. FF3 α, CAPM α, FFC4 α, and FF5 α are daily returns adjusted by the Fama-French 3-factor model, CAPM model, Fama-French-Carhart 4-factor model, and Fama-French 5-factor model, respectively. β_{Rm-Rf}, β_{SMB} and β_{HML} are risk exposures on excess market return, SMB and HML factors. All factor loadings are estimated using daily returns from Jan. 1, 2018. to June 30, 2020. *Turnover* is daily trading volume divided by total shares outstanding. Panel B presents variables related to COVID-19 shocks. *COVID Shock* indicates days on which COVID-19-related news triggered S&P 500 index to move by more than 2.5%. *Positive (negative) COVID Shock* indicates days on which COVID-19-related news triggered the S&P 500 index to move up (down) by more than 2.5%. Panel C summarizes measures of partisanship. *Red* is a dummy variable that equals 1 if the firm is headquartered in a Republican county. *Red (state)* indicates whether the firm is headquartered in a Republican state. *% Rep Vote (county /state)* is the percentage of votes received by the Republican Party at the county/state level. *Social-Connection-based Partisanship (SCP)* is the logarithm of a weighted sum of the Republican voting shares, where the weight is the Social Connectedness Index between the county of interest and other counties based on Facebook friendship links (excluding own county). All voting shares are measured using the 2016 presidential election data. Panel D displays summary statistics of local variables. *ΔVisits* is the change in non-essential visits since the beginning of 2020. For each county, we replace non-essential visit with its 5-day moving average to eliminate weekly seasonality. *Social Distancing Behavior (SDB)* is the demeaned change in visits to non-essential businesses. *New Cases* is the number of new COVID-19 cases per 1,000 residents in a state on a day. *% Unemp* is the state-level weekly new unemployment claim rate. *Lockdown* indicates whether there is a state-level "shelter-in-place," "non-essential services closure," or "closing of public venues" order in effect on a day. *% Female* is the percentage of women in a county. *HH Income* is the median household income in the past 12 months. *Total Religiosity Ratio (TRR)* is the proportion of a county's total population that attends church. Panel E shows firm characteristics. *ME* is the market value in millions of dollars on December 31, 2019. *BE* is the book value in millions of dollars for the fiscal year ending in 2019. *B/M* is the book-to-market ratio. *S&P 500* is a dummy variable that equals 1 if the stock is a S&P 500 index constituent December 31, 2019. *Institutional Ownership* equals the shares of stocks held by institutional investors divided by total shares outstanding. *ROA* is income before extraordinary items divided by total assets. Following Novy-Marx (2013), *gross profitability* is calculated as returns on gross profits (revenues minus cost of goods sold) scaled by total assets. *ΔROA* is the year-over-year change in ROA, and *ΔProfitability* is the year-over-year change in gross profitability.

	N	Mean	STD	Min	P25	P50	P75	Max
Panel A: stock performance (%)								
Raw return	380,309	-0.008	5.44	-23.7	-2.37	0	2.20	22.1
Excess return	380,309	-0.011	5.44	-23.7	-2.37	-0.006	2.20	22.1
FF3 α	380,309	0.045	4.05	-37.0	-1.63	-0.036	1.52	37.1
CAPM α	380,309	-0.034	4.39	-37.0	-1.89	-0.13	1.60	38.3
FFC4 α	380,309	0.039	4.01	-35.5	-1.63	-0.035	1.52	33.1
FF5 α	380,309	0.051	3.99	-37.6	-1.61	-0.032	1.52	36.1
Turnover	380,311	1.29	1.99	0.001	0.37	0.72	1.36	14.2
β_{Rm-Rf}	380,339	0.93	0.33	-0.63	0.77	0.97	1.15	1.87
β_{SMB}	380,339	0.78	0.61	-1.19	0.34	0.77	1.20	2.95
β_{HML}	380,339	0.31	0.59	-1.65	-0.074	0.30	0.72	2.21

(Table 1 continued)

	N	Mean	STD	Min	P25	P50	P75	Max
Panel B: COVID Shocks								
COVID Shock	380,339	0.22	0.42	0	0	0	0	1
Pos. COVID Shock	380,339	0.10	0.31	0	0	0	0	1
Neg. COVID Shock	380,339	0.12	0.33	0	0	0	0	1
Panel C: partisanship measures								
Red	377,212	0.20	0.40	0	0	0	0	1
Red state	379,339	0.41	0.49	0	0	0	1	1
% Rep Vote (county)	377,212	37.0	16.4	4.30	23.8	37.2	45.8	91.4
% Rep Vote (state)	379,339	45.5	9.61	4.30	35.3	47.2	52.7	75.7
SCP	378,212	15.7	0.75	14.5	15.1	15.6	16.3	18.8
Panel D: local variables								
ΔVisits	359,780	-0.39	0.30	-0.86	-0.67	-0.45	-0.087	0.10
SDB	359,780	0	0.10	-0.78	-0.05	-0.008	0.04	0.81
New Cases	376,295	0.074	0.15	-0.19	0	0.028	0.086	1.85
% Unemp	379,339	14.0	14.4	0.34	1.80	10.4	20.9	84.2
Lockdown	380,339	0.43	0.50	0	0	0	1	1
% Female	377,212	51.0	0.91	45.8	50.5	51.0	51.6	54.3
HH Income ($1000)	377,212	68.1	18.0	29.5	54.4	64.4	79.9	114.3
TRR	376,836	0.51	0.11	0.17	0.44	0.50	0.60	1.22
Panel E: firm characteristics								
ME ($ million)	380,339	10,281.4	50,514.3	0	249.0	1,072.3	4,331.3	1,304,764.8
B/M	380,214	0.57	0.83	-10.5	0.20	0.45	0.81	17.5
S&P 500	380,339	0.14	0.35	0	0	0	0	1
Inst. Own.	380,339	0.54	0.32	0	0.27	0.52	0.85	1.15
ROA (%)	379,435	-2.44	7.72	-43.6	-2.65	0.11	1.00	7.68
Profitability (%)	333,000	4.50	7.57	-26.1	1.32	4.73	8.21	25.7
ΔROA (%)	373,978	-0.83	5.57	-29.3	-1.54	-0.19	0.40	19.7
ΔProfitability (%)	327,419	-1.24	4.17	-20.4	-2.11	-0.45	0.26	12.6

Table 2. Firms in Republican and Democratic Counties

This table presents summary statistics for firms headquartered in Republican and Democratic counties. Republican (Democratic) counties are defined as counties where the Republican candidate received more (fewer) votes than the Democratic candidate in the 2016 presidential election. The sample period is from Jan. 1, 2020, to June 30, 2020. We restrict our sample to stocks listed on Nasdaq, NYSE and Amex. We exclude companies that have no book value in the fiscal year ending in 2019 or no market value at the end of 2019. We also exclude stocks whose price falls below $1 during the sample period. Panel A presents firm characteristics. ME is the market value in millions of dollars as of Dec. 31, 2019; BE is the book value in millions of dollars for the fiscal year that ended in 2019; BE/ME is the book-to-market ratio; β_{Rm-Rf}, β_{SMB} and β_{HML} are risk exposures estimated using daily returns from Jan. 1, 2018, to June 30, 2020. Panel B displays the number of firms by Fama-French 12 industry. Panel C lists the distribution of firm headquarters by state. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: firm characteristics

	Republican		**Democrat**		**Difference (Dem. - Rep.)**	
Variable	**Frequency**	**Mean**	**Frequency**	**Mean**	**Diff.**	**T-stat**
ME ($ mil)	607	4489.83	2,420	11570.86	7081.03***	3.10
BE ($ mil)	607	1770.19	2,420	3560.694	1790.50**	2.53
BE/ME	607	0.66	2,419	0.55	-0.11***	-3.12
β_{Rm-Rf}	607	0.88	2,420	0.95	0.066***	4.44
β_{SMB}	607	0.76	2,420	0.78	0.021	0.75
β_{HML}	607	0.49	2,420	0.26	-0.23***	-8.46

Panel B: industry distribution

	Rep.		**Dem.**		**Total**	
Fama-French 12 industry	**Freq.**	**Pct.**	**Freq.**	**Pct.**	**Freq.**	**Pct.**
Consumer Non-Durables	26	4.28	91	3.76	117	3.87
Consumer Durables	15	2.47	50	2.07	65	2.15
Manufacturing	69	11.37	186	7.69	255	8.42
Oil, Gas, and Coal Extraction and Product	25	4.12	64	2.64	89	2.94
Chemicals and Allied Products	11	1.81	53	2.19	64	2.11
Business Equipment	72	11.86	407	16.82	479	15.82
Telephone and Television Transmission	7	1.15	48	1.98	55	1.82
Utilities	17	2.80	58	2.40	75	2.48
Wholesale, Retail, and Some Services	44	7.25	203	8.39	247	8.16
Healthcare, Medical Equipment, and Drug	58	9.56	521	21.53	579	19.13
Finance	179	29.49	457	18.88	636	21.01
Other (Mines, Constr, Trans, Hotel, etc.)	84	13.84	282	11.65	366	12.09
Total	**607**	**100.00**	**2,420**	**100.00**	**3,027**	**100.00**

(Table 2 continued)

Panel C: headquarters distribution

State	Freq.	State	Freq.	State	Freq.
California	536	Michigan	49	Delaware	13
New York	293	Wisconsin	49	Nebraska	12
Texas	274	Arizona	45	Hawaii	10
Massachusetts	209	Indiana	44	Rhode Island	10
Pennsylvania	146	Tennessee	42	New Hampshire	9
Illinois	134	Missouri	36	Idaho	8
New Jersey	119	Nevada	30	Maine	8
Florida	116	Utah	25	Mississippi	8
Ohio	99	Oklahoma	19	West Virginia	7
Virginia	86	Iowa	17	District of Columbia	6
Georgia	81	Kentucky	17	South Dakota	5
Colorado	71	Louisiana	17	North Dakota	4
North Carolina	64	South Carolina	17	New Mexico	4
Minnesota	60	Kansas	16	Vermont	3
Connecticut	58	Alabama	15	Montana	2
Washington	54	Oregon	14	Wyoming	1
Maryland	52	Arkansas	13	**Total**	**3,027**

Table 3. Partisan Return Gap

This table presents the partisan return gap on COVID shock days from January 1, 2020, to June 30, 2020. The dependent variable is daily return adjusted by the Fama-French 3-factor model (3-factor α). COVID Shock equals to 1 if COVID-19-related news triggered the S&P 500 index to move by more than 2.5%. In panel A, we identify investors' partisanship by firm headquarters. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county where the Republican candidate received more votes in the 2016 presidential election. In Panel B, we measure partisanship using the social-connection-based partisanship (*SCP*). *SCP* is the log weighted sum of voting shares to the Republican Party, where the weight is the Social Connectedness Index between the county of interest and other counties based on Facebook friendship links. Control variables include county characteristics (*% Unemp, % Female, HH Income, TRR*), firm characteristics (*log(1+ME), B/M*), and their interactions with *COVID Shock* (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: partisanship by firm headquarters

	(1)	(2)	(3)
COVID Shock × Red	**0.19****	**0.20*****	**0.17****
	(2.49)	**(2.75)**	**(2.55)**
COVID Shock	-0.18*	-1.36	
	(-1.84)	(-0.68)	
Red	-0.03	-0.02	
	(-0.87)	(-0.82)	
Constant	0.08***	0.20	-0.04
	(2.73)	(0.28)	(-0.13)
Control variables	N	Y	Y
Firm, FF12 × Date FE	N	N	Y
R^2	0.000	0.002	0.044
Observations	377,182	376,431	376,430

Panel B: partisanship by social connections

	(1)	(2)	(3)
COVID Shock × SCP	**0.13****	**0.14****	**0.13****
	(2.37)	**(2.34)**	**(2.17)**
COVID Shock	-2.22**	-3.87	
	(-2.38)	(-1.43)	
SCP	-0.03	-0.02	
	(-1.60)	(-1.29)	
Constant	0.60*	0.68	-0.58
	(1.76)	(0.80)	(-1.17)
Control variables	N	Y	Y
Firm, FF12 × Date FE	N	N	Y
R^2	0.000	0.002	0.044
Observations	378,182	376,431	376,430

Table 4. Lockdown, COVID Cases, and Firm Fundamental

This table presents the partisan return gap after controlling fundamental measures of the impact of COVID-19. The dependent variable is Fama-French 3-factor alpha. *COVID Shock* equals to 1 if COVID-19-related news triggered the S&P 500 index to move by more than 2.5% on a day. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county where the Republican candidate received more votes in the 2016 presidential election. *Lockdown* indicates whether there is a state-level "shelter-in-place," "non-essential services closure," or "closing of public venues" in effect on a day. *New Cases* represents the number of new COVID-19 cases per 1,000 residents in a state on a day. *ΔProfitability* is the year-over-year change in gross profitability, where gross profitability is calculated as returns on gross profits (revenues minus cost of goods sold) scaled by total assets (Novy-Marx, 2013). We also include *ΔProfitability_missing* and its interaction with COVID Shock in the regression to preserve as many observations as possible. *ΔProfitability_missing* is a variable that equals 1 if *ΔProfitability* is missing. Control variables include *% Unemp, % Female, HH Income,* TRR, log*(1+ME), B/M*, and their interactions with *COVID Shock* (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
COVID Shock × Red	**0.21*****	**0.18****	**0.15****	**0.14****	**0.16*****	**0.15****
	(2.86)	**(2.60)**	**(2.60)**	**(2.45)**	**(2.71)**	**(2.51)**
COVID Shock	-2.43		-1.75		-2.82	
	(-1.25)		(-0.84)		(-1.40)	
Red	-0.02		-0.01		-0.01	
	(-0.73)		(-0.37)		(-0.28)	
Lockdown	0.02	0.03			0.02	0.03
	(0.56)	(1.02)			(0.49)	(0.91)
COVID Shock × Lockdown	0.38***	0.11			0.39***	0.11
	(3.22)	(1.45)			(3.32)	(1.51)
New Cases	0.02	0.17**			0.02	0.16**
	(0.13)	(2.48)			(0.12)	(2.45)
COVID Shock × New Cases	-0.49*	-0.49***			-0.49*	-0.47***
	(-1.95)	(-3.79)			(-1.95)	(-3.72)
ΔProfitability			1.03**	0.62	1.05**	0.68
			(2.41)	(1.25)	(2.45)	(1.36)
COVID Shock × ΔProfitability			-0.49	-0.61	-0.47	-0.64
			(-0.40)	(-0.56)	(-0.39)	(-0.59)
Constant	0.08	-0.23	0.38	-0.19	0.26	-0.37
	(0.11)	(-0.68)	(0.51)	(-0.51)	(0.34)	(-0.99)
Control variables	Y	Y	Y	Y	Y	Y
Firm, FF12 × Date FE	N	Y	N	Y	N	Y
R^2	0.002	0.044	0.002	0.044	0.002	0.044
Observations	373,410	373,409	376,431	376,430	373,410	373,409

Table 5. Firm Fundamentals

This table presents the partisan difference in changes in corporate earnings from 2020Q1 to 2021Q1. *ROA* is calculated as income before extraordinary items divided by total assets. Gross profitability is as returns on gross profits (revenues minus cost of goods sold) scaled by total assets (Novy-Marx, 2013). In columns (1) - (2), the dependent variable is *ΔROA*, the year-over-year change in ROA. In columns (3) - (4), the dependent variable is *ΔProfitability*, the year-over-year change in gross profitability. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county where the Republican candidate received more votes in the 2016 presidential election. We include *log(1+ME), B/M,* Past 12-month return, ΔROA_{q-4} and $\Delta Profitability_{q-4}$ as control variables (see Appendix A for definitions of these control variables). ΔROA_{q-4} and $\Delta Profitability_{q-4}$ are one-year lags of *ΔROA* and *ΔProfitability*. Robust standard errors are applied in all columns. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level.

	ΔROA		*ΔProfitability*	
	(1)	(2)	(3)	(4)
Red	**-0.12**	**0.02**	**-0.04**	**0.04**
	(-1.22)	**(0.26)**	**(-0.41)**	**(0.42)**
ΔROA_{q-4}	-30.86***	-31.79***		
	(-12.87)	(-13.30)		
$\Delta Profitability_{q-4}$			-18.79***	-20.28***
			(-9.13)	(-9.81)
Past 12-month return	0.82***	0.66***	0.53***	0.44***
	(9.80)	(7.13)	(10.79)	(8.27)
Log(1+ME)	-0.17***	-0.14***	0.01	0.00
	(-5.70)	(-4.73)	(0.70)	(0.03)
B/M	-0.39***	-0.19*	-0.05	0.04
	(-3.87)	(-1.95)	(-0.82)	(0.68)
Constant	1.39***	0.67*	-0.93***	-2.45***
	(4.90)	(1.68)	(-4.97)	(-7.25)
Quarter FE	N	Y	N	Y
FF12 FE	N	Y	N	Y
R^2	0.131	0.154	0.057	0.091
Observations	13,472	13,469	11,696	11,693

Table 6. Positive vs. Negative COVID News

This table presents the partisan return gap on positive and negative COVID shock days. The sample period is from Jan. 1, 2020, to June 30, 2020. The dependent variable is Fama-French 3-factor alpha. *Positive (negative) COVID Shock* indicates days on which COVID-19-related news triggered the S&P 500 index to move up (down) by more than 2.5%. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county where the Republican candidate received more votes in the 2016 presidential election. Control variables include *Lockdown, % Unemp, New Cases, % Female, HH Income, TRR, log(1+ME), B/M, ΔProfitability*, and their interactions with *Positive* and *Negative COVID Shock* (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Positive COVID Shock × Red	**0.30****	**0.24****	**0.22****
	(2.18)	**(2.37)**	**(1.98)**
Negative COVID Shock × Red	**0.09***	**0.09****	**0.09****
	(1.71)	**(2.01)**	**(2.05)**
Positive COVID Shock	-0.16	-5.93**	
	(-0.98)	(-2.03)	
Negative COVID Shock	-0.20*	-0.59	
	(-1.83)	(-0.24)	
Red	-0.03	-0.01	
	(-0.87)	(-0.28)	
Constant	0.08***	0.26	-0.39
	(2.73)	(0.34)	(-1.05)
Controls, Interactions	N	Y	Y
Firm, FF12 × Date FE	N	N	Y
R^2	0.000	0.003	0.044
Observations	377,182	373,410	373,409

Table 7. Social Distancing Behavior and Stock Returns

This table presents the social distancing behavior and risk-adjusted returns on COVID shock days from Jan. 1, 2020, to June 30, 2020. We exclude stocks operating in industries whose NAICS code = 71 or 72. Panel A presents the relation between social distancing behavior and stock returns. Panel B presents the partisan return gap explained by social distancing behavior. The dependent variable is Fama-French 3-factor alpha. COVID *Shock* indicates days on which COVID-19-related news triggered the S&P 500 index to move by more than 2.5%. *Social Distancing Behavior (SDB)* is the demeaned change in visits to non-essential businesses compared to visits at the beginning of 2020. For each county, we first calculate the 5-day moving average of non-essential visits to eliminate weekly seasonality and divide it by the number of visits at the beginning of 2020. We then demean by subtracting the daily average from each observation. Control variables include *Lockdown, % Unemp, New Cases, %Female, HH Income, TRR, log(1+ME), B/M, ΔProfitability*, and their interactions with *COVID Shock*. See Appendix A for definitions of control variables. Standard errors are clustered by date. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: the relation between social distancing behavior and stock returns

	(1)	(2)	(3)
COVID Shock × SDB	**1.04****	**0.88****	**0.95****
	(2.48)	**(2.35)**	**(2.52)**
COVID Shock	-0.14*	-2.79	
	(-1.75)	(-1.33)	
SDB	-0.14	0.04	0.02
	(-0.94)	(0.27)	(0.12)
Constant	0.09***	0.21	-0.38
	(3.28)	(0.25)	(-0.95)
Controls, Interactions	N	Y	Y
Firm, FF12 × Date FE	N	N	Y
R^2	0.000	0.002	0.043
Observations	350,947	349,519	349,519

Panel B: partisan return gap explained by social distancing behavior

	(1)	(2)	(3)	(4)
COVID Shock × Red	**0.11***	**0.08**	**0.18****	**0.14****
	(1.85)	**(1.54)**	**(2.51)**	**(2.44)**
COVID Shock × SDB	**0.88****	**0.80****		
	(2.16)	**(2.13)**		
COVID Shock	-0.17*		-0.17*	
	(-1.90)		(-1.88)	
Red	-0.03		-0.03	
	(-1.08)		(-0.88)	
SDB	-0.09	0.04		
	(-0.60)	(0.33)		
Constant	0.09***	-0.43	0.08***	-0.28
	(3.14)	(-1.09)	(2.76)	(-0.81)
Control variables	N	Y	N	Y
Firm FE, FF12 × Date FE	N	Y	N	Y
R^2	0.000	0.043	0.000	0.043
Observations	349,995	349,519	367,928	364,479

Table 8. Partisan Disagreement from StockTwits

This table presents the partisan return gap on days with large vs. small partisan disagreement between Republican investors and other investors. The sample period is from Jan. 1, 2020, to June 30, 2020. *Partisan disagreement* is measured as the difference in sentiment between Republican investors and other investors based on textual analyses of StockTwits posts. The dependent variable is Fama-French 3-factor alpha. *COVID Shock* indicates days on which COVID-19-related news triggered the S&P 500 index to move by more than 2.5%. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county where the Republican candidate received more votes in the 2016 presidential election. Control variables include *Lockdown, % Unemp, New Cases, % Female, HH Income, TRR, log(1+ME), B/M, ΔProfitability*, and their interactions with *COVID Shock* (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	Large partisan disagreement			Small partisan disagreement		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID Shock × Red	**0.34****	**0.29*****	**0.27****	**0.03**	**0.03**	**0.03**
	(2.57)	**(2.93)**	**(2.59)**	**(0.52)**	**(0.61)**	**(0.60)**
COVID Shock	-0.17	-3.80		-0.19**	-2.14	
	(-0.98)	(-1.16)		(-2.28)	(-0.89)	
Red	-0.09**	-0.05		0.04	0.04	
	(-2.08)	(-1.54)		(1.27)	(1.38)	
Constant	0.16***	0.91	-0.29	0.00	-0.60	-0.48
	(3.04)	(0.74)	(-0.42)	(0.19)	(-0.68)	(-1.33)
Controls	N	Y	Y	N	Y	Y
Firm, FF12×Date FE	N	N	Y	N	N	Y
R^2	0.000	0.003	0.052	0.000	0.002	0.047
Observations	189,927	186,795	186,794	187,255	186,615	186,615

Table 9. Firm Size and Index Constituent

This table presents subsample analyses based on firm size and S&P 500 index. Panel A splits the sample by median ME. Panel B partitions the sample by whether the stock is an S&P 500 index constituent. The dependent variable is Fama-French 3-factor alpha. *COVID Shock* indicates days on which COVID-19-related news triggered S&P500 to move by more than 2.5%. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county. Control variables include *Lockdown, % Unemp, New Cases, % Female, HH Income, TRR, log(1+ME), B/M, ΔProfitability,* and their interactions with *COVID Shock* (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: by size

	High ME (large stock)			Low ME (small stock)		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID Shock × Red	**0.10**	**0.07**	**0.08**	**0.30*****	**0.19*****	**0.16****
	(1.44)	**(1.06)**	**(1.06)**	**(2.92)**	**(2.71)**	**(2.16)**
COVID Shock	0.06	0.87		-0.44***	-6.55***	
	(0.58)	(0.31)		(-3.13)	(-2.94)	
Red	-0.01	-0.01		-0.05	0.01	
	(-0.31)	(-0.57)		(-1.19)	(0.36)	
Constant	0.03	0.10	0.12	0.14***	0.61	-0.88**
	(0.85)	(0.13)	(0.24)	(3.08)	(0.59)	(-2.02)
Controls	N	Y	Y	N	Y	Y
Firm, FF12×Date FE	N	N	Y	N	N	Y
R^2	0.000	0.001	0.081	0.001	0.004	0.045
Observations	188,356	186,597	186,597	188,826	186,813	186,812

Panel B: by S&P 500

	S&P 500			Non-S&P 500		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID Shock × Red	**-0.12***	**-0.06**	**-0.08**	**0.24*****	**0.16****	**0.16****
	(-1.67)	**(-0.87)**	**(-1.06)**	**(2.77)**	**(2.56)**	**(2.41)**
COVID Shock	0.09	3.40		-0.23**	-4.17**	
	(0.93)	(1.02)		(-2.17)	(-2.21)	
Red	0.04	0.03		-0.04	-0.01	
	(1.61)	(1.01)		(-1.17)	(-0.26)	
Constant	0.00	-0.80	0.48	0.10***	0.52	-0.65
	(0.03)	(-0.82)	(0.83)	(2.94)	(0.63)	(-1.65)
Controls	N	Y	Y	N	Y	Y
Firm, FF12 × Date FE	N	N	Y	N	N	Y
R^2	0.000	0.002	0.154	0.000	0.003	0.043
Observations	53,808	53,254	53,253	323,374	320,156	320,155

Table 10. Institutional Ownership and Turnover Ratio

This table presents subsample analyses based on institutional ownership and turnover ratio. Panel A divides the sample by median institutional ownership as of 2019Q4. Panel B partitions the sample based on median turnover on each trading day. *Turnover* is the daily trading volume divided by total shares outstanding. The dependent variable is FF3 alpha. *COVID Shock* indicates days on which COVID-19-related news triggered S&P500 to move by more than 2.5%. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county. Control variables include *Lockdown, % Unemp, New Cases, % Female, HH Income, TRR, log(1+ME), B/M, ΔProfitability*, and their interactions with *COVID Shock* (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: by institutional ownership

	High institutional ownership			Low institutional ownership		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID Shock × Red	**0.10**	**0.11**	**0.12**	**0.28*****	**0.17****	**0.15****
	(1.16)	**(1.28)**	**(1.31)**	**(2.84)**	**(2.43)**	**(2.13)**
COVID Shock	-0.11	-2.58		-0.26**	-2.71	
	(-0.89)	(-0.91)		(-2.48)	(-1.48)	
Red	0.03	0.04		-0.07**	-0.03	
	(1.01)	(1.35)		(-2.01)	(-1.16)	
Constant	0.06*	0.30	-0.29	0.11***	0.28	-0.41
	(1.78)	(0.31)	(-0.50)	(3.28)	(0.37)	(-1.12)
Controls	N	Y	Y	N	Y	Y
Firm, FF12 × Date FE	N	N	Y	N	N	Y
R^2	0.000	0.001	0.061	0.001	0.004	0.043
Observations	188,304	186,545	186,541	188,878	186,865	186,865

Panel B: by turnover ratio

	High turnover			Low turnover		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID Shock × Red	**0.04**	**0.05**	**0.05**	**0.26*****	**0.18****	**0.17****
	(0.44)	**(0.66)**	**(0.65)**	**(2.83)**	**(2.59)**	**(2.45)**
COVID Shock	-0.30*	-5.54*		-0.06	0.20	
	(-1.70)	(-1.77)		(-0.57)	(0.13)	
Red	0.01	0.03		-0.00	0.00	
	(0.31)	(0.99)		(-0.13)	(0.14)	
Constant	0.23***	1.07	-0.94	-0.07***	-1.23**	0.03
	(4.30)	(0.85)	(-1.40)	(-2.70)	(-2.34)	(0.09)
Controls	N	Y	Y	N	Y	Y
Firm, FF12 × Date FE	N	N	Y	N	N	Y
R^2	0.001	0.004	0.074	0.000	0.003	0.051
Observations	188,553	186,584	186,485	188,629	186,826	186,765

Table 11. Local Income and Education

This table presents subsample analyses based on income and education. Panel A divides the sample based on median household income. A county is classified as *High Income* if its median household income in the past 12 months is above the cross-sectional median across all counties in the sample. Panel B partitions the sample based on the percentage of population below a bachelor's degree. The dependent variable is FF3 alpha. Control variables include *Lockdown, % Unemp, New Cases, % Female, HH Income, TRR, log(1+ME), B/M, ΔProfitability,* and their interactions with *COVID Shock* (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: by income

	High Income			Low Income		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID Shock × Red	**-0.09**	**-0.03**	**-0.03**	**0.29*****	**0.22*****	**0.21****
	(-0.96)	**(-0.29)**	**(-0.31)**	**(2.87)**	**(2.77)**	**(2.59)**
COVID Shock	-0.19*	-2.73		-0.17*	-2.96	
	(-1.78)	(-1.31)		(-1.75)	(-0.90)	
Red	0.05	0.05		-0.05	-0.03	
	(1.39)	(1.42)		(-1.39)	(-0.92)	
Constant	0.09***	0.42	-0.36	0.08**	0.32	-0.36
	(2.62)	(0.55)	(-0.87)	(2.37)	(0.28)	(-0.59)
Controls	N	Y	Y	N	Y	Y
Firm, FF12 × Date FE	N	N	Y	N	N	Y
R^2	0.000	0.003	0.041	0.000	0.002	0.056
Observations	190,628	188,477	188,476	186,554	184,933	184,931

Panel B: by education

	High Education			Low Education		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID Shock × Red	**-0.00**	**0.04**	**0.04**	**0.23*****	**0.18****	**0.17****
	(-0.04)	**(0.33)**	**(0.35)**	**(2.68)**	**(2.60)**	**(2.32)**
COVID Shock	-0.19*	-2.47		-0.18*	-2.18	
	(-1.85)	(-1.07)		(-1.73)	(-0.79)	
Red	0.05	0.05		-0.04	-0.02	
	(1.36)	(1.23)		(-1.46)	(-0.86)	
Constant	0.08**	0.22	-0.29	0.08***	0.13	-0.25
	(2.46)	(0.25)	(-0.64)	(2.65)	(0.13)	(-0.45)
Controls	N	Y	Y	N	Y	Y
Firm, FF12 × Date FE	N	N	Y	N	N	Y
R^2	0.000	0.002	0.045	0.000	0.002	0.052
Observations	188,500	186,367	186,365	188,682	187,043	187,042

Table 12. Placebo Test

This table presents the partisan return gap on days with large market movements from Jan. 1, 2018, to Dec. 31, 2019. We restrict our sample to stocks listed on Nasdaq, NYSE, and Amex. We exclude companies that have no book value in the fiscal year ending in 2017 and 2018, no market value by the end each year, and stocks whose price falls below $1 during the sample period. The dependent variable is Fama-French 3-factor alpha. Factor loadings are estimated using daily returns from Jan. 1, 2018, to June 30, 2020. *Jump day* indicates days on which S&P 500 moves by more than 2.5%. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county. Control variables include *% Unemp, % Female, HH Income, TRR, log(1+ME), B/M, ΔProfitability*, and their interactions with *COVID Shock* (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Jump day × Red	**-0.009**	**0.004**	**0.015**
	(-0.15)	**(0.09)**	**(0.30)**
Jump day	0.009	-1.650	
	(0.13)	(-1.57)	
Red	0.013^{*}	0.014^{**}	
	(1.85)	(2.14)	
Constant	-0.005	-0.041	2.149^{***}
	(-0.62)	(-0.20)	(10.36)
Controls	N	Y	Y
Firm, FF12 × Date FE	N	N	Y
R^2	0.000	0.000	0.034
Observations	1,450,820	1,439,121	1,439,121

Table 13. Robustness

This table shows several robustness tests. Panel A presents alternative return benchmarks: CAPM alpha, Fama-French-Carhart 4-factor alpha, and Fama-French 5-factor alpha. Factor loadings are estimated using daily returns from Jan. 1, 2018. To June 30, 2020. Panel B presents alternative event thresholds. In column (1), we exclude government-policy-related dates. In column (2), we consider days on which S&P 500 moves by more than 2.5%, regardless of the reason. In columns (3) – (5), we consider days on which S&P 500 moves by more than 2%, 3%, and 5%. At these thresholds, there are 38, 26, and 10 shock days. Panel C presents alternative partisan measures and industries. In column (1), *Rep Vote % (county)* measures the share of votes to the Republican Party in a county. In column (2), *Red (state)* indicates whether a firm is headquartered in a Republican state. Column (3) excludes firms in the finance and utilities industries (FF12 = 8 or 11). Column (4) exclude companies in the wholesale, retail and some services industry (FF12 = 9). Control variables include *Lockdown, Unemp, New Cases, % Female, HH Income, TRR, log(1+ME), B/M, ΔProfitability,* and their interactions with *COVID Shock*. Control variables, firm fixed effects, and industry × date fixed effects are included in all columns of all panels. Standard errors are clustered by date. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Alternative return benchmarks

	(1) CAPM	(2) Fama-French-Carhart	(3) Fama-French 5
COVID Shock × Red	**0.15****	**0.15****	**0.13****
	(2.49)	**(2.54)**	**(2.31)**
Constant	-0.66	-0.42	-0.31
	(-1.65)	(-1.14)	(-0.87)
Controls, Firm FE, FF12 × Date FE	Y	Y	Y
R^2	0.125	0.042	0.040
Observations	373,409	373,409	373409

Panel B: Alternative thresholds

	(1) All ≥ 2.5%	(2) ≥ 2%	(3) ≥ 3%	(4) ≥ 5%
COVID Shock × Red	**0.14*****	**0.12****	**0.16****	**0.24****
	(2.65)	**(2.49)**	**(2.60)**	**(2.21)**
Constant	-0.45	-0.30	-0.53	-0.23
	(-1.14)	(-0.72)	(-1.56)	(-0.82)
Controls, Firm FE, FF12 × Date FE	Y	Y	Y	Y
R^2	0.044	0.043	0.044	0.044
Observations	373,409	373,409	373,409	373,409

Panel C: Alternative partisanship measures & industries

	(1) Rep Vote % (county)	(2) Red (state)	(3) No finance & utilities	(4) No wholesale & retail
COVID Shock × Partisan	**0.004***	**0.10***	**0.16****	**0.13****
	(1.89)	**(1.88)**	**(2.39)**	**(2.29)**
Constant	-0.52	-0.26	-0.98*	-0.35
	(-1.15)	(-0.71)	(-1.82)	(-0.92)
Controls, Firm FE, FF12 × Date FE	Y	Y	Y	Y
R^2	0.044	0.044	0.044	0.044
Observations	373,409	373,409	285,557	343,028

Internet Appendix for

"Partisan Return Gap: The Polarized Stock Market in the Time of a Pandemic"

October 2021

This Internet Appendix provides additional tables used in the paper.

List of Tables

Table IA1. Partisanship and social distancing behavior

This table presents the effect of partisanship on individual social distancing behavior. In Panel A, we consider the following regression:

$$SDB_{i,t} = \alpha + \beta_1 ln(1+Cases_{i,t}) + \beta_2 Red_i + \beta_3 ln(1+Cases_{i,t}) \times Red_i + \sum_{j=1}^{n} \gamma_i X_{i,t}^j + \mu_i + \gamma_t + \epsilon_{i,t}$$

In Panel B, we replace $ln(1+Cases_{i,t})$ with *Lockdown*. The dependent variable is *Social Distancing Behavior (SDB)*, the demeaned change in visits to non-essential businesses compared to visits at the beginning of 2020. For each county, we first calculate the 5-day moving average of non-essential visits to eliminate weekly seasonality and divide it by the number of visits at the beginning of 2020. We then demean by subtracting the daily average from each observation. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county where the Republican candidate received more votes in the 2016 presidential election. We control for *ln(1+cases), Lockdown, % Unemp, % Female, HH Income*, and *TRR* in both panels. *Ln(1+Cases)* is the log form of one plus the cumulative COVID-19 cases in a county. *Lockdown* is a dummy that equals 1 if a state-level "shelter in place," "non-essential services closure," or "closing of public venues" order is in effect. *% Unemp* is the state-level weekly new unemployment claim rate. *% Female* is the percentage of women in a county. *HH Income* is the median household income in the past 12 months. *TRR* is the proportion of a county's total population that attends church. Standard errors are double clustered at the county and date levels. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: response to COVID-19 cases

	(1)	(2)	(3)	(4)
Ln(1+cases)	0.01***	-0.00	0.00	-0.03***
	(5.15)	(-0.40)	(0.92)	(-9.79)
Red		0.03***	0.01	
		(3.79)	(1.48)	
Ln(1+cases) × Red		**0.02*****	**0.03*****	**0.02*****
		(11.16)	**(12.16)**	**(10.99)**
Constant	0.05***	0.02***	0.49**	0.16***
	(7.37)	(3.93)	(2.30)	(15.69)
Controls	N	N	Y	Y
County, Date FE	N	N	N	Y
R^2	0.030	0.260	0.328	0.715
Observations	59,199	58,842	58,723	58,723

Panel B: response to lockdown orders

	(1)	(2)	(3)	(4)
Lockdown	0.03***	-0.01	-0.06***	-0.08***
	(3.05)	(-1.10)	(-5.61)	(-6.80)
Red		0.07***	0.06***	
		(6.32)	(5.12)	
Lockdown × Red		**0.07*****	**0.09*****	**0.05*****
		(5.48)	**(6.43)**	**(4.56)**
Constant	0.07***	0.02***	0.37*	0.19***
	(7.61)	(4.84)	(1.72)	(17.70)
Controls	N	N	Y	Y
County, Date FE	N	N	N	Y
R^2	0.010	0.157	0.271	0.685
Observations	59,199	58,842	58,723	58,723

Table IA2. Government policy and earnings announcements

This table presents the partisan return gap after excluding COVID news days that may confound with other mechanisms. Column (1) excludes shocks related to government policies about federal aid. Column (2) excludes stock-level observations on their earnings announcement dates. Column (3) excludes observations on days surrounding firm-level earnings announcements ([t-1, t+1]). The dependent variable is Fama-French 3-factor alpha. *COVID Shock* indicates days on which COVID-19-related news triggered the S&P 500 index to move by more than 2.5%. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county where the Republican candidate received more votes in the 2016 presidential election. Control variables include *Lockdown*, *% Unemp*, *New Cases*, *%Female*, *HH Income*, *TRR*, *log(1+ME)*, *B/M*, *ΔProfitability*, and their interactions with COVID Shock (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1) Exclude days w/ gov. policy	(2) Exclude earnings announcements	(3) Exclude earnings announcements [t-1, t+1]
COVID Shock × Red	**0.14*****	**0.16****	**0.15****
	(2.63)	**(2.54)**	**(2.36)**
Constant	-0.19	-0.38	-0.32
	(-0.87)	(-1.01)	(-0.83)
Controls, Firm FE, FF12 × Date FE	Y	Y	Y
R2	0.044	0.044	0.045
Observations	373,409	367,421	355,550

Table IA3. Analyst coverage and analyst forecast

This table presents the partisan return gap after controlling for analyst coverage and analyst forecast. The dependent variable is Fama-French 3-factor alpha. *COVID Shock* indicates days on which COVID-19-related news triggered the S&P 500 index to move by more than 2.5%. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county where the Republican candidate received more votes in the 2016 presidential election. *Analyst coverage* is the number of analysts that cover a firm. *Analyst forecast* is average forecast of analysts. Control variables include *Lockdown*, *% Unemp*, *New Cases*, *%Female*, *HH Income*, *TRR*, *log(1+ME)*, *B/M*, *ΔProfitability*, and their interactions with COVID Shock (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
COVID Shock	-0.20	-2.47	
	(-1.61)	(-1.19)	
Red	-0.03	0.01	
	(-0.88)	(0.30)	
COVID Shock × Red	**0.22********	**0.13****	**0.13****
	(2.80)	**(2.22)**	**(2.19)**
Analyst coverage	-0.00	0.01**	-0.00
	(-0.77)	(2.05)	(-0.08)
COVID Shock × Analyst coverage	0.01	-0.04**	-0.04***
	(0.48)	(-2.16)	(-2.64)
Analyst forecast	0.00	0.01	-0.02
	(0.06)	(1.26)	(-0.91)
COVID Shock × Analyst forecast	0.03**	0.00	0.01
	(2.10)	(0.37)	(0.73)
Constant	0.09***	0.08	-0.35
	(2.69)	(0.09)	(-0.84)
Controls	N	Y	Y
Firm, FF12 × Date FE	N	N	Y
R^2	0.000	0.002	0.050
Observations	326,982	323,960	323,958

Table IA4. Labor force telework flexibility

This table presents the partisan return gap after controlling for labor force telework flexibility (LFTF). The dependent variable is Fama-French 3-factor alpha. *COVID Shock* indicates days on which COVID-19-related news triggered the S&P 500 index to move by more than 2.5%. *Red* is a dummy that equals 1 if the firm is headquartered in a Republican county where the Republican candidate received more votes in the 2016 presidential election. *LFTF* is the labor force telework flexibility at the 4-digit NAICS industry level, as defined in Favilukis et al. (2020). Control variables include *Lockdown*, *% Unemp*, *New Cases*, *%Female*, *HH Income*, *TRR*, *log(1+ME)*, *B/M*, *ΔProfitability*, and their interactions with COVID Shock (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. $*$, $**$, $***$ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
COVID Shock	-0.76	-3.60	
	(-0.90)	(-1.41)	
Red	-0.03	-0.01	
	(-0.84)	(-0.27)	
COVID Shock × Red	**0.17****	**0.12****	**0.10***
	(2.13)	**(2.00)**	**(1.69)**
LFTF	-0.04	-0.06*	
	(-1.43)	(-1.85)	
COVID Shock × LFTF	0.11	0.12	0.04
	(0.74)	(0.83)	(0.28)
Constant	0.32*	0.73	-0.42
	(1.84)	(0.83)	(-0.75)
Controls	N	Y	Y
Firm, FF12 × Date FE	N	N	Y
R^2	0.000	0.002	0.054
Observations	343,341	300,130	300,129

Table IA5. Lockdown, COVID Cases, and Firm Fundamental (SCP)

This table presents the social-connection-based partisan return gap after controlling fundamental measures of the impact of COVID-19. The dependent variable is Fama-French 3-factor alpha. *COVID Shock* equals to 1 if COVID-19-related news triggered the S&P 500 index to move by more than 2.5% on a day. The social-connection-based partisanship (*SCP*) is the log weighted sum of voting shares to the Republican Party, where the weight is the Social Connectedness Index between the county of interest and other counties based on Facebook friendship links. *Lockdown* indicates whether there is a state-level "shelter-in-place," "non-essential services closure," or "closing of public venues" in effect on a day. *New Cases* represents the number of new COVID-19 cases per 1,000 residents in a state on a day. *ΔProfitability* is the year-over-year change in gross profitability, where gross profitability is calculated as returns on gross profits (revenues minus cost of goods sold) scaled by total assets (Novy-Marx, 2013). Control variables include *% Unemp, % Female, HH Income,* TRR, log*(1+ME), B/M*, and their interactions with *COVID Shock* (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
COVID Shock	-4.39*		-3.63		-4.17*	
	(-1.72)		(-1.40)		(-1.70)	
SCP	-0.02		-0.01		-0.01	
	(-1.17)		(-0.80)		(-0.67)	
COVID Shock × SCP	**0.12****	**0.12****	**0.10****	**0.11****	**0.08***	**0.10***
	(2.05)	**(2.06)**	**(2.09)**	**(2.05)**	**(1.72)**	**(1.93)**
Lockdown	0.02	0.03			0.02	0.02
	(0.57)	(0.94)			(0.50)	(0.84)
COVID Shock × Lockdown	0.37***	0.11			0.38***	0.12
	(3.15)	(1.49)			(3.27)	(1.55)
New Cases	0.02	0.16**			0.02	0.16**
	(0.10)	(2.34)			(0.11)	(2.33)
COVID Shock × New Cases	-0.43*	-0.41***			-0.45*	-0.41***
	(-1.71)	(-3.34)			(-1.76)	(-3.33)
ΔProfitability			1.02**	0.62	1.04**	0.68
			(2.40)	(1.24)	(2.44)	(1.35)
COVID Shock × ΔProfitability			-0.45	-0.60	-0.44	-0.63
			(-0.37)	(-0.55)	(-0.36)	(-0.58)
ΔPb_missing			-0.14	-0.11	-0.14	-0.09
			(-1.58)	(-0.75)	(-1.54)	(-0.62)
COVID Shock × ΔPb_missing			0.50*	0.42*	0.51**	0.42*
			(1.97)	(1.97)	(2.02)	(1.95)
Constant	0.52	-0.70	0.66	-0.65	0.50	-0.77
	(0.59)	(-1.40)	(0.79)	(-1.23)	(0.59)	(-1.45)
Controls	Y	Y	Y	Y	Y	Y
Firm, FF12 × Date FE	N	Y	N	Y	N	Y
R^2	0.002	0.044	0.002	0.044	0.002	0.044
Observations	373,410	373,409	376,431	376,430	373,410	373,409

Table IA6. Partisan Disagreement from StockTwits (SCP)

This table presents the social-connection-based partisan return gap on days with large vs. small partisan disagreement between Republican investors and other investors. The sample period is from January 1, 2020, to June 30, 2020. *Partisan disagreement* is measured as the difference in sentiment between Republican investors and other investors based on textual analyses of StockTwits posts. The dependent variable is Fama-French 3-factor alpha. *COVID Shock* indicates days on which COVID-19-related news triggered the S&P 500 index to move by more than 2.5%. The social-connection-based partisanship (*SCP*) is the log weighted sum of voting shares to the Republican Party, where the weight is the Social Connectedness Index between the county of interest and other counties based on Facebook friendship links. Control variables include *Lockdown, % Unemp, New Cases, % Female, HH Income, TRR, log(1+ME), B/M, ΔProfitability*, and their interactions with *COVID Shock* (see Appendix A for definitions of these control variables). Standard errors are clustered by date. T-statistics are reported in parentheses. ∗, ∗∗, ∗∗∗ indicate significance at the 10%, 5%, and 1% level, respectively.

	Large partisan disagreement			Small partisan disagreement		
	(1)	(2)	(3)	(4)	(5)	(6)
COVID Shock	-3.26*	-6.00		-1.18	-2.74	
	(-2.00)	(-1.51)		(-1.29)	(-0.95)	
SCP	-0.07**	-0.04*		0.01	0.02	
	(-2.24)	(-1.77)		(0.24)	(0.67)	
COVID Shock × SCP	**0.20****	**0.15***	**0.18***	**0.06**	**0.03**	**0.03**
	(2.09)	**(1.82)**	**(1.93)**	**(1.13)**	**(0.56)**	**(0.65)**
Constant	1.26**	1.68	-0.95	-0.08	-0.79	-0.62
	(2.38)	(1.25)	(-0.99)	(-0.20)	(-0.77)	(-1.33)
Controls	N	Y	Y	N	Y	Y
Firm, FF12×Date FE	N	N	Y	N	N	Y
R^2	0.000	0.003	0.052	0.000	0.002	0.047
Observations	190,431	186,795	186,794	187,751	186,615	186,615