Stock reactions of the S&P500 industries to negative and positive COVID-19 news

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Abstract

Purpose – This paper aims to use the Covid-19 pandemic situation to conduct an experiment-like study that focuses on industry reactions under stress. Particularly, this study analyzes stock response to eight pandemic related news in 2020 across different industries. This study also investigates the role that the market risk, beta, plays in such stock reactions.

Design/methodology/approach – This study computes the cumulative abnormal returns (CAR) around COVID-19 events using adjusted daily stock returns of all stocks in the S&P 500 index between January 2, 2020 and December 31, 2020. This study also sorts all stocks by beta into quintiles and measures the CAR [0, +3] for each quintile around each event date.

Findings – This study finds that low beta portfolios exhibit greater abnormal returns (in absolute value) than high beta portfolios during down markets while high beta portfolios exhibit greater abnormal returns (in absolute values) when the market starts to recover. However, this study finds that beta does not seem to explain the abnormal returns reported in various industries during times of negative sentiment. During times of positive sentiment, both the beta effect and industry effect are present.

Originality/value – Extant literature almost unanimously concurs that the COVID-19 pandemic has brought about negative stock reactions to financial markets across the globe. Nevertheless, three interrelated issues have not been explored: market reactions during the subsequent recovery, industry heterogeneity and individual stocks' risk profile. The study addresses these matters.

Keywords Investments, Beta, COVID-19, Pandemic, US industries, Negative and positive news

Paper type Research paper

1. Introduction

Most major US stock indices lost almost a third of their values in about a month (February 22 to March 23, 2020) due to COVID-19. Nevertheless, a relentless recovery during the second half of 2020 re-gained and surpassed the losses of the first half. Extant literature focuses on overall stock market performance amidst the early stages of the pandemic, which is inherently marked with predominantly negative news. For example, Topcu and Gulal (2020) and Liu *et al.* (2020) show that international stock market indices were negatively affected by COVID-19 during its early stage. Ashraf (2020a) finds that stock markets performed poorly along with the growth in confirmed COVID-19 cases. However, it does not examine much of the subsequent recovery. The literature also overlooks industry heterogeneity and does not consider the potential role of stock-specific characteristics. In contrast, we focus on immediate reactions to breaking news, negative and positive; and we explore stock reactions in different S&P500 industries. Further, we test the explanatory

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power of individual stocks' risk profiles in understanding industry reactions during the crisis.

Moskowitz and Grinblatt (1999) posit that stocks in a particular industry move together because they are subject to similar market and regulatory conditions. Accordingly, we propose that when bad news arrives, investors would haste to move wealth to "safer" industries without considering the characteristics of individual stocks. Broad asset allocation dominates individual stock selection. This behavioral bias is documented in the literature. During the 1987 stock market crash, investments shifted from risky to safe assets (Caballero and Krishnamurthy, 2008). Similarly, when good news arrives, we anticipate investors to quickly move wealth to industries where greater upswings are expected. Reactions to good news are rarely investigated in the literature. We anticipate observing homogenous intra-industry reactions and heterogenous inter-industry reactions. Further, we test a hypothesis that a stock's individual risk profile is not an important determinant of swift investment decisions made under stressful conditions.

Empirically, we analyze the daily cumulative abnormal returns (CAR) of all stocks listed in the S&P500 index around several dates of significant COVID-19 announcements. Our analysis spans over the Year 2020, which was inundated with negative pandemic news in the first half and positive news in the second half. First, we examine the CAR of various industries around eight prominent COVID-19 pandemic-related events [1]. We specifically test whether the industry reaction is explained by anticipated shocks in the corresponding product markets. For instance, we test a sub-hypothesis that bad news must instigate negative reactions in the consumer discretionary industry because investors forecast a drop in demand. Second, we perform a single sorted portfolio analysis to analyze the potential beta effect. We sort all stocks by their betas to test whether stocks with higher market betas exhibit relatively stronger reactions. Third, we apply double sorted portfolio analysis to disentangle the industry effect from the beta effect. We sort stocks within each industry by their betas and examine the pandemic's impact across the beta-industry sorts to see how the two effects simultaneously impact the studied reactions to pandemic news.

Our work contributes to the literature in a few ways. First, we define the pandemic in broader terms. We gauge the market immediate reaction to the pandemic news, positive and negative, during a wide time window that comprises several critical dates, extending the existing studies (Topcu and Gulal, 2020; Ashraf, 2020a). Second, we compare stock reactions across different industries in light of plausible shifts in the corresponding product market. Several studies have analyzed the impact of COVID-19 on the entire stock market; but very little attention has been paid to industry heterogeneity. Third, we test whether individual stock's beta explains the reaction of stocks during abnormal conditions of noneconomic origin.

The rest of this paper unfolds as follows. Section 2 presents relevant literature and develops the hypotheses. Section 3 explains the data and the methodology. Section 4 discusses the findings and Section 5 concludes the paper.

2. Literature review and hypotheses development

2.1 Literature review

The reaction of the stock markets to crises, disasters and similar catastrophic events is well-documented, albeit not well-explained. Authors have explored a wide spectrum of events including the 9/11 tragedy (Nikkinen *et al.*, 2008), aviation disasters (Kaplanski and Levy, 2010), hurricanes (Lanfear *et al.*, 2018), natural disasters (Ragin and Halek, 2016; Bai *et al.*, 2019), financial crises (Laura *et al.*, 2016; Guidolin *et al.*, 2019) and warfare (Yin, *et al.*, 2020). Not surprisingly, health-related crises have also been considered by several authors

(Chen *et al.*, 2007). Collectively, these studies have documented evidence that catastrophic events cause distinct movements, often downward, in stock prices.

The current COVID-19 has not gone unnoticed by scholars. Several authors have documented the impact of the COVID-19 pandemic on the financial markets. Salisu and Vinh (2020) found that the more concerning the health news received by investors are, the greater the negative impact on stock prices. Hanke *et al.* (2020) found that the negative stock market reaction to the pandemic was intensified in countries with higher death cases. Haroon and Rizvi (2020) analyze the relationship between sentiment and volatility of equity markets. They found evidence of panic behavior associated with increasing volatility. Mazur *et al.* (2020) show that the pandemic instigates a negative reaction in 90% of the stocks listed in the S&P1500. Tiberiu (2020) uses the S&P500 stocks and reports similar findings. Ali *et al.* (2020) show that even the traditionally safe investment avenues, e.g. gold, do not survive the downward wage. Narayan and Phan (2020) study the impact of COVID-19 on the stock markets in different countries and report similar results. Using daily data from 77 countries from January 22 to April 17, 2020, Ashraf (2020b) finds that the announcements of government social distancing measures have a direct negative effect on stock market returns. Topcu and Gulal (2020) find that the pandemic had a statistically significant negative impact on Turkey's stock market up until April 10, 2020, only. The outbreak's pessimistic effect on the stock market had begun to taper off during the second half of April.

Chahuán-Jiménez *et al.* (2021) find that countries with better institutional and economic conditions weather the pandemic better than other countries with less developed economies. Also, Ahundjanov *et al.* (2020) study the impact of Google searches related to the COVID-19 pandemic on the global financial indices. They find that a one unit increase in the search queries results in a cumulative decline in global financial markets of up to 0.07% in one day and up to 0.15% in one week. In addition, Czech *et al.* (2021) examine the impact of Covid on the alternative energy markets. Compared with traditional ones, the alternative energy market weathered the pandemic better and was characterized by relatively lower volatility. Liu *et al.* (2020) show that 21 leading stock market indices were negatively affected by COVID-19 in the beginning of the COVID-19 outbreak and Asian stock markets took extra hit than other countries. Ashraf (2020a) finds that between January 22 and April 17, 2020, the negative stock market performance is associated with the growth in confirmed COVID-19 cases and such negative relation is stronger during the early days and 40 and 60 days after the first confirmed cases. Heyden and Heyden (2021) find that stock markets in the USA and Europe performed significantly poorly at the announcement of the first COVID-19 related death. Goodell and Huynh (2020) investigate how COVID-19 affects 49 US industries in the first two months of 2020, showing positive abnormal returns for the medical and pharmaceutical products industry and negative abnormal returns for the restaurants, hotels and motels industry.

2.2 Industry reactions to COVID-19 pandemic news

The studies listed in the literature review above almost unanimously concur that the COVID-19 pandemic has brought about negative market reactions. Nevertheless, very little attention has been paid to subsequent recovery, industry heterogeneity and stocks' individual risk profile.

We extend the literature by filling several gaps in this study. First, we consider both the first hit (during the first quarter of 2020) and the recovery (during the past two quarters of 2020). Second, we argue that stocks exhibit industry-specific effects because firms in the same industry operate under similar regulations and market conditions (Moskowitz and Grinblatt, 1999). Further, we argue that industry-level movements are governed by investors' anticipation. In down markets, investors search for safe heavens. In up markets, investors try to embark on industries with greater upward potential. This behavior is well-documented in the literature. For instance, gold is widely considered a safe haven in both developed and emerging countries during market turmoil (Kinateder *et al.*, 2021). Besides gold, several assets, such as commodities and currencies, provide shelter for equity markets during crises (Grisse and Nitschka, 2015; Henriksen, 2018; Hasan *et al.*, 2021). As such, it is quite reasonable to suspect that when market conditions change, investors transfer funds across industries in pursuit of more desirable risk-return combinations. In fact, a few industries are named after their unique covariation with the rest of the market. For instance, stocks in the consumer cyclical (or consumer discretionary) industry are known to move in unison with the rest of the market; while stocks in the consumer noncyclical (consumer nondiscretionary, defensive or staples) industry tend to be somewhat independent of market movements. Accordingly, we analyze the behavior of the 11 industries of the S&P500 index during the COVID-19 pandemic period; and we test the following overarching hypothesis:

H1. During times of abnormal market conditions (very high/low sentiment) investors move funds across industries to maximize return and/or minimize losses.

In this study we focus on immediate reactions rather than long-term reactions. We gauge the industry reaction to bad and good news as the media plays a major part in the volatility of the stock market. For instance, Baker *et al.* (2020) found that during past health crises, next-day newspaper accounts did not attribute a single major stock market movement to infectious disease outbreaks or pandemic-related developments. However, at the start of the COVID-19 crisis, from February 24 to April 20, 2020, newspapers attributed two dozen such jumps to coronavirus-related developments even though the excess mortality rate from COVID-19 (as of June 23, 2020) is a fraction of the mortality rates of previous health crises (e.g. Spanish Flue and the influenza pandemics of 1957–1958 and 1968). Further, they state that the earliest stock market movements in late February and early March mostly involve reactions to news about the course of the pandemic in the USA. Later movements in March through the end of April 2020 also reflect policy responses to the pandemic, including news about actual or prospective fiscal and monetary policy actions. Although reaction to negative news (i.e. crises) is well-document, there is little research on positive news and corresponding investors' reactions. Table 1 lists the 11 industries included in the S&P500 index and their predicted reactions to COVID-19 news.

The predictions are based on the pandemic's potential impact on core business activities and supply and demand forces in the product and services markets. A certain inter-industry reaction may not always be driven by business operations. Investment reallocation may as well play a significant role in the market movements. For instance, during the pandemic and under the pressure of negative news, investors may decide to move funds from high-risk industries to safer ones. The target industries may exhibit a positive reaction due to the increased demand for stocks, and not necessarily because business conditions have improved. The table describes the predicted reactions of different industries to negative news and the rationale for each. These predicted reactions are the focus of the testable hypotheses in this paper. Except for the information technology industry, which seems to be always in high demand, positive news is expected to trigger opposite reactions.

2.3 Individual stock risk profile

The COVID-19 pandemic was associated with an unprecedented high frequency of news arrival (Haroon and Rizvi, 2020). Arguably, this has left investors with very little time to analyze stocks individually. For that reason, they are likely to take actions at the aggregate industry level (Lee *et al.*, 2002). We test whether a stock risk profile is associated with the

Table 1. Predictions of industries reactions to news

Industry	Predicted reaction to negative news	Rationale of reaction to negative news	Predicted reaction to positive news	Hypotheses
Information technology	Positive	Increased demand in the products and services markets (e.g. the demand for automation and remote access technology).	Positive	H2-1
Health care	Positive	Increased demand in the products and services markets (e.g. the demand for health care services, vaccines and medication).	Negative	H2-2
Consumer discretionary	Negative	Decreased demand in the products and services markets. Aggregate discretionary spending increases in good economic conditions and decreases in bad economic conditions.	Positive	H2-3
Communication services	Positive	Increased demand in the products and services markets (e.g. the demand for internet and tools of connectivity).	Negative	H2-4
Financials	Negative	Decreased demand for stocks. Financials are known to be relatively risky stocks. The average beta of all stocks in the financial industry in the sample is 1.23 (the second highest).	Positive	H2-5
Industrials	Negative	Decreased demand in the products and services markets.	Positive	H2-6
Consumer staples	Positive	Increased demand for stocks. Consumer defensive stocks are known to remain stable during times of financial turmoil. The average beta of all stocks in the staples industry in the sample is 0.73 (the lowest).	Negative	H2-7
Utilities	Positive	Increased demand for stocks. Utilities stocks are known to be relatively less risky. The average beta of all stocks in the utility industry in the sample is 0.97.	Negative	H2-8
Real estate	Negative	Decreased demand in the product and services markets. Real estate is cyclical.	Positive	H2-9
Materials	Negative	Decreased demand in the product and services markets. Materials are known to be cyclical.	Positive	H2-10
Energy	Negative	Decreased demand in the product and services markets. Decreased demand for stocks. Energy stocks are known to be relatively risky. The average beta of all stocks in the energy industry in the sample is 1.36 (the highest).	positive	H2-11

Note: We did not supply a separate rationale for positive news reactions because it is a simple inverse of the ones applied to negative news, except for the information technology magnitude of the industry reaction. That is, we test whether the industry reaction is consistent with the notion that stocks with high betas tend to react more drastically than those with low betas. Chan and Lakonishok (1993) argue that high beta stocks perform much worse than low beta stocks in market downswings and vice versa. Similarly, Estrada and Vargas (2012) find that high beta portfolios fall significantly more than low beta portfolios during negative black swans (market index falling by more than 5% in one month). Formally, we test the following hypothesis:

H3. Stocks with larger betas exhibit stronger reactions to COVID-19 pandemic news.

3. Data and methodology

The sample includes all companies listed in the S&P500 index on January 1, 2020. We use the center for research in security prices to obtain adjusted daily stock returns of all stocks between January 2, 2020 and December 31, 2020. To measure investors' reaction to an event, the standard approach is to compute the CAR around the event or announcement date (Mackinlay, 1997). In event studies, it is crucial to determine the event point precisely. When studying the COVID-19 pandemic, this is a challenge. The crisis started in Wuhan-China in late 2019 as an endemic. Gradually, it developed into an epidemic that led to a complete lockdown on January 23, 2020. Parallel to its development in China, COVID-19 was gradually becoming a pandemic, i.e. a global health concern. In the USA, although it is almost impossible to identify the exact date when the pandemic commenced, the following are a few specific dates when major COVID-19 news – with a potential negative impact on investors' sentiment – broke out: [2]

- Date 1: January 21 – The Centers for Disease Control and Prevention (CDC) confirms first USA coronavirus case.
- Date 2: February 3 – the USA declares public health emergency.
- Date 3: February 25 – CDC says COVID-19 is heading toward pandemic status.
- Date 4: March 13 – President Trump declares COVID-19 a national emergency and imposes travel ban on nonUS citizens traveling from Europe.

The latter date, March 13, is marked with the administration's most significant COVID-19 related declaration that had meaningful practical implications on the economy. Not surprisingly, the date was followed by Black Monday (March 16th) which witnessed one of the largest one-day losses in market history. We also identify the following four dates when major positive news broke out:

(1) Date 5: July 27 – Moderna vaccine begins third phase trial and receives $472m from the government. On the same date, the Senate introduced the HEALS Act, which is an upbeat package of several bills that comprises supportive policies on health, economic assistance, liability protection and schools.

(2) Date 6: August 11 – the government agrees to pay $1.5bn to purchase 100 million doses of the Moderna vaccine.

(3) Date 7: November 16 – Moderna announces spectacular vaccine efficacy results (94.5%). The US Food and Drug Administration (FDA) announces that it will move swiftly to clear Pfizer's and Moderna's vaccines for emergency use.

(4) Date 8: December 11 – The FDA agrees to an emergency use authorization for the Pfizer and BioNTech vaccine, allowing shipments to begin.

Conceivably, December 11 is associated with the most significant positive news because it marks the official approval of vaccines. During this study period, there are two phases of stock market movements, in that, there is a downward trend until mid-July after which stock prices start ascending above their original beginning-of-the-year levels.

3.1 Cumulative abnormal returns

To measure stock reactions around specific COVID-19 event dates, we compute the CAR. For each stock i, the abnormal return on day t is computed as follows [3]:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \qquad i = 1 \ldots 505 \qquad t = 1 \ldots 125 \tag{1}$$

where $R_{i,t}$ is the observed return and $E(R_{i,t})$ is the expected return computed using the three-factor model of Fama and French. The factor loadings of Fama and French model are obtained from Professor French's website [4]. The parameters of the model are estimated using a 180-day estimation period ending 20 days before the first event date. Active trading days, not calendar days, are used. Abnormal returns on each date are then computed with model parameters and concurrent market data. It is important to note that the estimation window of the model parameters (three factor loadings of the Fama-French model) does not include the high volatility period induced by the pandemic that could distort the estimation (Khotari and Warner, 2006).

Then, the CAR for each stock is computed as follows:

$$CAR_{i,\ [T_1,T_2]} = \sum\nolimits_{t=T_1}^{t=T_2} AR_{i,t} \tag{2}$$

Where $[T_1,T_2]$ represents the event window. Given the purpose of this study, we use several event windows [0, +1], [0, +2] and [0, +3]. Longer event windows may not be informative because the stock reaction would be contaminated by other news (Khotari and Warner, 2006).

3.2 Sorted portfolios

We apply single-sort and double-sort techniques. Sorted portfolio techniques are used to analyze the behavior of the studied variable across a few tranches of the sample ranked by a key variable. Double sorting disentangles the effects of two key variables on the studied variable. A monotonic trend is interpreted as evidence of a significant impact of the key variable(s) on the studied variable.

In the single-sorting case, we sort the stocks in the sample by their betas. Then, we split the sample into five quintiles where quintile five includes stocks with the highest betas. For each quintile, we compute the average CAR [0, +3] and examine the relationship between beta and CAR. In the double-sorting case, however, we rank the stocks within each industry by their betas and then split them into terciles (tercile three includes the stocks with the highest betas). This results in a total of 11x3 groups sorted on industry then beta. We then compute the average CAR [0, +3] for each group to examine the extent of their reaction to the COVID-19 news.

4. Empirical results

4.1 Descriptive statistics

The table below shows the descriptive statistics of the sample. We report the mean, maximum, minimum and standard deviation of daily stock returns. We also report the same statistics for 11 subsamples representing the industries within the S&P500 index. (Table 2)

Table 2.
Descriptive statistics

	Sample	Information technology	Health care	Consumer discretionary	Communication services	Financials	Industrials	Consumer staples	Utilities	Real estate	Materials	Energy
# Firms	505	73	63	61	26	65	73	32	28	31	28	25
% of Sample	100%	14.46%	12.48%	12.08%	5.15%	12.87%	14.46%	6.34%	5.54%	6.14%	5.54%	4.95%
# Obs.	127765	18469	15939	15433	6578	16445	18469	8096	7084	7843	7084	6325
Average	0.08%	0.17%	0.07%	0.12%	0.11%	0.03%	0.06%	0.05%	0.03%	0.02%	0.11%	–0.09%
Maximum (%)	27.74	20.30	13.25	16.13	15.55	19.87	19.23	14.47	21.75	15.01	18.11	27.74
Minimum (%)	–46.32%	–31.91	–15.09%	–20.78	–22.00	–25.77	–19.40	–23.11	–22.37%	–26.88	–21.91	–46.32%
Std Div	8.22%	7.18%	5.60%	5.67%	5.57%	8.27%	7.32%	4.79%	6.81%	6.90%	6.59%	10.13%
Avg. beta	1.02	1.07	0.83	0.93	0.88	1.23	1.08	0.73	0.97	1.07	1.03	1.36
Alpha	0.000%	0.026%	0.021%	0.049%	0.034%	–0.157%	–0.091%	–0.014%	–0.033%	–0.008%	–0.003%	–0.241%

Notes: The table shows standard descriptive statistics of daily adjusted returns between January 1 and December 31, 2020, of all stocks included in the S&P500 index as of January 1, 2020. Although it is called the S&P500, the index contains 505 stocks because five of its component companies have two share classes of stock. In the interest of consistency, minor changes in the S&P500 index composition after January 1, 2020, are disregarded. We report the average, maximum, minimum and standard deviation of daily adjusted returns of all stocks in the sample as well as within each industry. We also report the average beta and the average Jensen's alpha for each industry

The sample includes 505 stocks and 127,765 data points (trading days). The average daily return of all stocks is 8 basis points. The worst and best performers belong to the energy industry (–46.32% and 27.74%). The sample has a beta of 1.02 and an extremely small Jensen's alpha which is quite reasonable for a well-diversified portfolio. The highest beta is that of the energy industry (1.36) followed by the financial industry (1.23); and the lowest is that of the consumer staples (0.73) followed by health care (0.83). The lowest Jensen's alpha is that of the energy industry (–0.241%) followed by the financial industry (–0.157%); and the highest is that of the consumer discretionary industry (0.049%) followed by the communication services industry (0.034%).

4.2 Reactions to negative news

The first four columns in Table 3 below shows the CAR distribution by industry around four dates when negative news broke out. The CARs are estimated using one-, two- and three-day postevent windows.

Overall, the results in Table 3 support several predictions outlined in Table 1 above, with a few exceptions. First, we look for consistent behavior on all four event dates. For the information technology industry, we observe positive CARs in all four dates (this is consistent with *H2*-1). On the other hand, four other industries reported negative CARs for at least three out of four dates, as anticipated, namely, consumer discretionary (*H2*-3), financials (*H2*-5), real estate (*H2*-9) and energy (*H2*-11). However, contrary to our expectations, communication services (*H2*-4) and staples (*H2*-7) did not fare well for the most part. In addition, materials (*H2*-10), utilities and health care, had mixed reactions. Moreover, we observe that the CAR [0, +3] is most significant in Date 4 for a couple of reasons. First, Date 4 seems to be the most important event date as a major decision was enacted by the white house (declaration of a national emergency and travel ban). Second, it is because the market reaction to news of such magnitude may not settle on the first day. In fact, Welch (2020) reports that, during the pandemic, the Robinhood investors have collectively increased their stock holdings particularly about four days after a major market movement. He also reports that the increase in holdings during the pandemic was irrelevant to whether the news was good or bad. As such, we focus our attention on the three-day cumulative return CAR [0, +3].

The industry that is most affected by the negative news is the energy industry [*H2*-11] with a CAR [0, +3] on Date 4 being –11.41% followed by the real estate industry [*H2*-9] with a CAR [0, +3] of –4.98%. The consumer discretionary industry comes into third place with a negative reaction [*H2*-3] of –4.27%. On the other hand, the utilities and the consumer staples industries exhibit high positive reactions [*H2*-8 and *H2*-7] with the CAR [0, +3] on Date 4 being 8.07% and 7.32%, respectively. The information technology and the health care industries also reacted positively, as expected [*H2*-1 and *H2*-2], but to a lesser degree than the utilities and the consumer staples industries. An intriguing exception is the communication services industry that exhibited relatively weak negative reactions to the negative news although it is expected to have had positive reactions given the anticipated increased demand for such services in a period when people are confined in their homes (*H2*-4). The CAR [0, +3] on Date 4 is –0.58%. Although the communications industry had negative CAR for Dates 1, 2 and 4, it did react positively in Date 3 (pandemic status confirmed) with CAR [0, +3] being 0.97%.

Notice that three industries exhibit consistent reactions throughout the four negative news dates studied, namely, the information technology (positive), the consumer discretionary (negative) and the energy markets (negative). For all other industries, the

Table 3. Reactions to negative and positive News – cumulative abnormal returns

		21-Jan	3-Feb	25-Feb	13-Mar	27-Jul	11-Aug	16-Nov	11-Dec
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		First COVID-19 Case Reported	Public Health Emergency Declared	Pandemic Status Confirmed	National Emergency/ Travel Ban	Moderna Vaccines Advances and HEALS Act	Sizable Government Purchase of Promising Moderna Vaccines	Vaccine Research Advances. FDA Signals Quick Approval.	Vaccines Approved. Shipping to begin.
Industry	**CAR (%)**	**Date 1**	**Date 2**	**Date 3**	**Date 4** (%)	**Date 5**	**Date 6**	**Date 7**	**Date 8**
Information technology	CAR [0, +1]	0.3035	0.9950	0.8320	–1.0560	–0.5054	0.7522	–0.0707	0.8008
	CAR [0, +2]	0.6277	0.3538	0.1232	–0.6698	–0.4087	0.9882	0.0684	1.0636
	CAR [0, +3]	1.0961	0.8855	1.7398	1.0653	0.5251	0.9102	0.4269	1.5263
Health care	CAR [0, +1]	0.0795	0.5018	0.2806	0.0100	0.4000	0.5033	–0.2776	–0.4133
	CAR [0, +2]	–0.5418	1.4775	0.5072	1.3177	0.4026	0.5207	–1.2056	–0.4182
	CAR [0, +3]	–1.4862	1.2688	–0.1235	2.2590	–0.0011	0.3177	–1.6256	–0.8800
Consumer discretionary	CAR [0, +1]	–0.1228	0.3744	–0.4879	–1.5241	–0.4340	–0.0301	–0.0257	0.5056
	CAR [0, +2]	–0.1291	–0.2194	–0.4533	–3.3223	–0.6290	0.0706	0.3208	0.5979
	CAR [0, +3]	–0.7269	–0.8033	–0.3759	–4.2748	–0.4081	0.0310	0.3978	1.0392
Communication services	CAR [0, +1]	–0.1125	–0.3002	0.1070	–0.8270	–0.4985	–0.0693	0.0286	0.0335
	CAR [0, +2]	–0.6529	–1.1556	–0.0103	–1.7640	–0.7024	0.5794	–0.0047	–0.3072
	CAR [0, +3]	–1.1022	–0.2311	0.9727	–0.5836	–0.1286	0.5435	0.2285	–0.5857
Financials	CAR [0, +1]	0.4143	–0.7221	–0.1086	1.1723	0.7034	–1.8390	0.6013	–0.4666
	CAR [0, +2]	0.1721	0.0555	1.2016	–0.6070	1.2079	–2.0641	1.2370	–0.1906
	CAR [0, +3]	0.1733	–0.3245	–0.3365	–2.5697	0.0271	–1.4869	1.2387	–0.0763
Industrials	CAR [0, +1]	–0.4676	0.3645	–0.2599	1.6511	0.0946	–1.0935	0.3448	–0.7354
	CAR [0, +2]	0.5840	0.9142	0.8740	–0.1085	0.3684	–1.3105	1.2356	–0.6438
	CAR [0, +3]	1.1837	0.9682	0.0248	–1.8035	–0.1408	–0.8129	1.1535	–1.3631
Consumer staples	CAR [0, +1]	0.0711	–0.4838	–0.2727	2.0274	0.8578	0.2803	–0.3383	–0.0520
	CAR [0, +2]	–0.0919	–0.4929	–1.0869	6.0738	0.1035	0.3670	–0.8495	–0.7475
	CAR [0, +3]	–0.1011	–0.5510	–2.4456	7.3234	0.3930	0.3783	–0.8552	–0.6699
Utilities	CAR [0, +1]	0.3169	–2.4233	–0.6124	0.3521	2.1754	0.1163	–1.4620	–0.0560
	CAR [0, +2]	1.1270	–3.0774	–0.7743	7.3373	1.4611	0.1852	–2.2576	0.6887
	CAR [0, +3]	2.3054	–3.3390	–3.2804	8.0676	1.8599	–0.6348	–3.6061	–0.6068
Real estate	CAR [0, +1]	–0.8231	–0.2955	–0.4557	–3.1760	2.7168	–0.2299	0.5735	–0.2426
	CAR [0, +2]	0.0207	–1.5662	–1.3773	–3.5115	3.2887	–1.1635	0.1238	0.1329
	CAR [0, +3]	0.8460	–1.4862	–2.9537	–4.9849	2.8781	–0.8855	–0.1287	–0.0214

(*continued*)

		21-Jan	3-Feb	25-Feb	13-Mar	27-Jul	11-Aug	16-Nov	11-Dec
Materials	CAR [0, +1]	–0.7070	0.3427	–0.1134	2.2922	–1.5246	–0.8502	0.1289	–0.8158
	CAR [0, +2]	–1.1057	1.0517	–0.3095	1.7800	–1.9877	–0.6518	0.5004	–0.3354
	CAR [0, +3]	–0.8826	0.4853	–0.5938	–0.6536	–3.5324	–0.5194	0.5120	–0.7967
Energy	CAR [0, +1]	–0.7623	–1.4288	–2.2651	2.8781	–0.5856	–0.6610	1.9156	–2.6697
	CAR [0, +2]	–1.0581	1.0473	–1.3855	–4.3237	0.0574	–2.0861	0.8186	–2.2139
	CAR [0, +3]	–0.7434	–0.1817	–0.1158	–11.4142	–3.1207	–0.8698	2.1626	–2.7071

Notes: For each stock we compute the abnormal return as the difference between observed returns and expected returns estimated using the three-factor model of Fama and French. The parameters of the model are estimated using a 180-day estimation period ending 20 days before the first event date. Cumulative abnormal returns are estimated over one-, two- and three-day postevent windows to make sure that they are not contaminated by other news (Khotari and Warner, 2006). Four negative and four positive pandemic-related news are considered. All numbers are statistically significant at the 5% or the 1% level of significance; all figures are in %

Table 3.

reaction was mixed across the various dates, with Date 4 being the dominant date with the most substantial reactions as expected.

4.3 Reactions to positive news

Columns 5–8 in Table 3 report one-, two- and three-day CAR for each industry around the four dates characterized by positive news.

The findings are a little less supportive of our hypotheses than those reported in Columns 1–4. Nevertheless, several hypotheses seem to hold very well. For the most part, the information technology and the consumer discretionary industries react positively to positive pandemic news as expected (*H2*-1 and *H2*-3). However, except for Date 7, the materials industry reacts negatively to the positive news, contrary to our expectations [*H2*-10]. Mixed results are observed for the rest of the industries. As mentioned earlier, market reactions may not settle swiftly after the arrival of the news and therefore, we pay special consideration to the three-day cumulative return because it is inclusive of the one-day and the two-day returns.

The results show that only one industry exhibits consistent reactions throughout the four positive news dates studied, namely, the information technology which reacted positively, as expected. For all other industries, the reaction was mixed across the various dates, with Date 8 having the most significant reactions. This does not come as a surprise because it is on this date that the vaccine was finally approved by the FDA and cleared for shipping, signaling the beginning of the end of the pandemic. The greatest reaction on this date is observed in the energy sector with a significant negative reaction to the positive news, contrary to our expectations. The second most significant reaction is observed in the information technology market which was positive in line with expectations. Overall, the reactions to the positive news are less prominent than the reactions to the negative news. Frazzini (2006) argues that the disposition effect leads to an underreaction to the news. He proposes that the less-than-expected reaction is attributed to gain realization behavior. When the stock starts to move up, in response to positive news, some investors decide to liquidate their positions. This behavior puts a downward pressure on prices and mitigates the original surge. We believe that this might be present in our sample because in July the market had regained almost all of the year-to-date losses. It is very plausible, therefore, that many investors who were previously riding their losses (refrain from selling to avoid realizing their losses), are tempted to sell at the good news to realize potential capital gains.

As previously mentioned, it would be difficult and perhaps futile to attempt to identify an exhaustive list of all COVID-19 related news and announcements. Nevertheless, for robustness, we have identified several other relevant dates pertaining to the World Health Organization (WHO) declarations and the attempts to reopen the economy [5]. The findings, available upon request, are not materially different.

4.4 Beta sorted portfolios

We now turn the discussion to the role of the sensitivity to market risk, *beta*. We sort all stocks, regardless of the industry, by *beta* into quintiles and measure the CAR [0, +3] for each quintile around each event date. As explained in the methodology section, in sorted portfolio analysis, a monotonic trend indicates the existence of a relationship between the two variables. The results, reported in Table 4 below, show that there is a strong monotonic trend in all four dates associated with positive pandemic news. In all four dates, the CAR increases steadily as we move from high-beta portfolios to low-beta portfolios (right to left). With negative news, monotonicity virtually disappears. We conclude that the beta effect is significant during times of rising markets with positive sentiments, but not during times of

	Beta-sorted portfolios					
	Low beta	**2**	**3**	**4**	**High beta**	**High Minus Low**
Avg. Beta	**0.82**	**0.9**	**1.02**	**1.15**	**1.32**	
# Obs.	**101**	**101**	**101**	**101**	**101**	
Negative News						
Date 1	−0.0412	−0.0408	−0.0526	−0.0501	−0.0888	−0.0476
Date 2	−0.2333	−0.1605	−0.1815	−0.2340	−0.1779	0.0554
Date 3	−0.0977	−0.0999	−0.1246	−0.0965	−0.0955	0.0022
Date 4	−0.0082	−0.0085	−0.0333	−0.0099	−0.0013	0.0069
Positive News						
Date 5	−0.0754	−0.0699	−0.0732	−0.0843	−0.1187	−0.0433
Date 6	−0.0427	−0.0713	−0.0946	−0.1491	−0.1392	−0.0965
Date 7	−0.0490	−0.0504	−0.0544	−0.0645	−0.0777	−0.0287
Date 8	−0.0576	−0.0668	−0.0725	−0.0732	−0.0880	−0.0304

Notes: In this table, we test whether reported industry reaction is in line with individual stocks risk profile (beta). In the interest of space and clarity, we limit the presentation to CAR [0, +3] only. We first conduct a single-sort test to examine whether the degree of industry's immediate reaction to negative or positive news is associated with the level of beta. We split the entire sample, regardless of industries, into quintiles according to the level of market risk beta and observe whether a trend in CAR exists. A monotonic trend signifies the presence of the beta effect. That is, a high-beta portfolio reacts more prominently than a low-beta portfolio. Statistical significance is reported with standard asterisk system were ***, ** and * denote statistical significance at the 1, 5 and 10% level, respectively; all figures are in %

Table 4. Risk profile effects

negative sentiments. This supports our proposition that during times of negative sentiment, investors do not concern themselves with individual stock characteristics. Nevertheless, the figures in Table 4 are derived from the whole sample, i.e. the industry effect may be masked. This notion is further explored in the next section.

4.5 Beta and industry sorted portfolios

The findings above may be contaminated with industry effects as the pandemic resulted in the abrupt shift in consumer demand for certain industries relative to others. Therefore, it seems that we do not gain much information from simply aggregating all stocks into groups according to their *betas* without considering the nature of the industry in which they operate. As such, we repeat this sorting of stocks according to their *betas*, but within each industry for consistency. A monotonic trend across beta terciles within an industry indicates that the beta effect exists within that industry. The first four columns in Table 5 show the CAR [0, +3] for each tercile (sorted according to *beta*) within each industry for four negative news dates. Also reported is the difference between the CAR [0, +3] of the highest *beta* stocks tercile (3) and the lowest beta stocks tercile (1).

The differences in the CAR between the two extreme terciles, whereas statistically significant in most cases, are inconsistent throughout the industries and event dates. We also do not observe any consistent monotonic trends across terciles of betas. In line with the previous findings under negative news, low *beta* stocks exhibit higher reactions than high *beta* stocks in four industries, namely, industrials, utilities, real estate and materials. On the other hand, high *beta* stocks report higher reactions than low *beta* stocks in the other seven industries. Given these inconsistent results, it seems that investors are more sensitive to the overall future outlook of the industry than they are to the measure of systematic risk, *beta*, of individual stocks. In other words, under abnormal stressful situations, investors consider

Table 5. Industry vs risk profile effects under negative and positive news

		Date 1 (1)	Date 2 (2)	Date 3 (3)	Date 4 (4)	Date 5 (5)	Date 6 (6)	Date 7 (7)	Date 8 (8)
Information technology	1 – Low Beta	1.3710%	1.1599%	2.2788%	1.3954%	0.5434%	0.9418%	0.3962%	1.4979%
	2	1.2934%	1.0449%	2.0530%	1.2571%	0.5602%	0.9709%	0.4554%	1.6282%
	3 – High Beta	1.0735%	1.2121%	2.3815%	1.4582%	0.5658%	1.0195%	0.4645%	1.7096%
	Diff. (3–1)	–0.2975% ***	0.0522% **	0.1027% **	0.0629% *	0.0224% ***	0.0777% ***	0.0683% **	0.2117% ***
Health care	1 – Low Beta	–1.5426%	1.1947%	–0.1163%	2.1270%	–0.0008%	0.2622%	–1.2613%	–0.6901%
	2	–1.5903%	1.3576%	–0.1321%	2.4171%	–0.0009%	0.2622%	–1.3418%	–0.7264%
	3 – High Beta	–1.4631%	1.4119%	–0.1374%	2.5138%	–0.0011%	0.2858%	–1.4223%	–0.8208%
	Diff. (3–1)	0.0795% *	0.2172% ***	–0.0211% *	0.3867% **	–0.0002% ***	0.0236% ***	–0.1610% ***	–0.1308% ***
Consumer discretionary	1 – Low Beta	–0.7778%	–0.6876%	–0.3218%	–3.6592%	–0.3774%	0.0231%	0.3418%	0.8832%
	2	–0.7778%	–0.8595%	–0.4022%	–4.5740%	–0.3812%	0.0289%	0.3716%	0.9706%
	3 – High Beta	–0.6611%	–0.8767%	–0.4102%	–4.6655%	–0.3660%	0.0330%	0.3790%	0.9415%
	Diff. (3–1)	0.1167% **	–0.1891% **	–0.0885% **	–1.0063% ***	0.0114% ***	0.0098% **	0.0372% ***	0.0582% ***
Communication services	1 – Low Beta	–0.9290%	–0.1857%	0.7817%	–0.4690%	–0.0911%	0.4138%	0.1880%	–0.4869%
	2	–1.0802%	–0.2265%	0.9533%	–0.5720%	–0.1125%	0.4756%	0.2000%	–0.5125%
	3 – High Beta	–1.0046%	–0.2016%	0.8484%	–0.5090%	–0.1091%	0.4661%	0.2160%	–0.5792%
	Diff. (3–1)	–0.0756% *	–0.0159% *	0.0667% **	–0.0400%	–0.0180% ***	0.0523% **	0.0280% ***	–0.0923% ***
Financials	1 –Low Beta	0.1548%	–0.2775%	–0.2877%	–2.1971%	0.0299%	–1.8270%	1.4459%	–0.0778%
	2	0.1647%	–0.3083%	–0.3197%	–2.4412%	0.0333%	–1.8270%	1.5220%	–0.0938%
	3 – High Beta	0.1433%	–0.2929%	–0.3037%	–2.3192%	0.0326%	–1.8818%	1.5828%	–0.1069%
	Diff. (3–1)	–0.0115% *	–0.0154% *	–0.0160% *	–0.1221% *	0.0027% ***	–0.0548% **	0.1370% ***	–0.0291% **
Industrials	1 – Low Beta	1.2000%	1.1398%	0.0292%	–2.1230%	–0.1304%	–0.7703%	1.0682%	–1.2477%
	2	1.2903%	1.0554%	0.0271%	–1.9658%	–0.1516%	–0.8753%	1.2421%	–1.4678%
	3 – High Beta	1.3161%	0.8654%	0.0222%	–1.6119%	–0.1440%	–0.9016%	1.2793%	–1.5266%
	Diff. (3–1)	0.1161% **	–0.2744% ***	–0.0070% *	0.5111% ***	–0.0136% ***	–0.1313% **	0.2112% ***	–0.2789% ***
Consumer staples	1 – Low Beta	–0.0903%	–0.4391%	–1.9486%	5.8353%	0.2827%	0.2555%	–0.6152%	–0.4131%
	2	–0.0971%	–0.5290%	–2.3477%	7.0305%	0.2885%	0.2777%	–0.6277%	–0.4917%
	3 – High Beta	–0.0903%	–0.4708%	–2.0895%	6.2571%	0.2769%	0.2944%	–0.6717%	–0.4721%
	Diff. (3–1)	0.0000%	–0.0317% *	–0.1409% **	0.4218% **	–0.0058% ***	0.0389% **	–0.0565% ***	–0.0590% ***
Utilities	1 – Low Beta	2.4668%	–3.3941%	–3.3345%	8.2007%	1.8121%	–0.6185%	–2.9513%	–0.5380%
	2	2.4668%	–3.5727%	–3.5100%	8.6324%	1.8121%	–0.6185%	–3.5135%	–0.5912%
	3 – High Beta	2.4421%	–3.3583%	–3.2994%	8.1144%	1.7578%	–0.7050%	–3.9000%	–0.6681%
	Diff. (3–1)	–0.0247% *	0.0357% *	0.0351% *	–0.0863% *	–0.0544% ***	–0.0866% **	–0.9486% ***	–0.1301% ***

(*continued*)

Table 5.

		Date 1 (1)	Date 2 (2)	Date 3 (3)	Date 4 (4)	Date 5 (5)	Date 6 (6)	Date 7 (7)	Date 8 (8)
Real estate	1 – Low Beta	0.7632%	–1.2686%	–2.5213%	–4.2552%	2.9550%	–0.8713%	–0.1101%	–0.0204%
	2	0.8206%	–1.4416%	–2.8651%	–4.8354%	3.0781%	–0.9470%	–0.1377%	–0.0229%
	3 – High Beta	0.6647%	–1.1821%	–2.3494%	–3.9650%	3.5091%	–0.9660%	–0.1349%	–0.0231%
	Diff. (3–1)	–0.0985% **	0.0865% **	0.1719% ***	0.2901% *	0.5541% ***	–0.0947% **	–0.0248% ***	–0.0027% ***
Materials	1 – Low Beta	–0.9545%	0.5249%	–0.6422%	–0.7068%	–2.9596%	–0.4997%	0.4713%	–0.7664%
	2	–0.9267%	0.5096%	–0.6235%	–0.6862%	–3.6538%	–0.5373%	0.5296%	–0.8241%
	3 – High Beta	–0.8248%	0.4841%	–0.5923%	–0.6519%	–3.7269%	–0.5588%	0.5137%	–0.8982%
	Diff. (3–1)	0.1297% ***	–0.0408% *	0.0499% *	0.0549%	–0.7673% ***	–0.0591% ***	0.0424% ***	–0.1319% ***
Energy	1 – Low Beta	–0.6947%	–0.1679%	–0.1070%	–10.5467%	–3.3838%	–0.9431%	2.8726%	–3.3390%
	2	–0.7806%	–0.1908%	–0.1215%	–11.9849%	–4.2298%	–1.1789%	2.9313%	–3.6693%
	3 – High Beta	–0.6557%	–0.1908%	–0.1215%	–11.9849%	–4.3144%	–1.1789%	3.2830%	–3.8527%
	Diff. (3–1)	0.0390% *	–0.0229% *	–0.0146% *	–1.4382% ***	–0.9306% ***	–0.2358% **	0.4104% **	–0.5137% *

Notes: In this table, we conduct a double-sort test to disentangle the industry effects from the beta effects with negative and positive news. To do so, we sort stocks by beta into terciles within each industry and report CAR [0, +3] for the resulting 11 X 3 portfolios. Statistical significance is reported with standard asterisk system were ***, ** and * denote statistical significance at the 1, 5 and 10% level, respectively industries' conditions more than they consider stocks' individual risk profiles. Under pressure to act fast, investors may have adjusted their asset allocations based on industry expectations with little attention to individual stock selection.

Columns 5–8 in Table 5 show the CAR [0, +3] for each tercile (sorted according to *beta*) within each industry for four positive news dates. We observe strong positive monotonic trends (in absolute values) in 34 industry-date pairs (out of 44). Those occasions are highlighted in red. This means that portfolios containing stocks of high betas react more drastically (positively or negatively) to positive pandemic news than low beta portfolios. Compared with our findings with negative news, this finding is more consistent with the theoretical implication of beta as a measurement of sensitivity to market movements. This finding corroborates our earlier finding that during periods of positive sentiments, both industry and beta effects exist.

4.6 Robustness checks

The findings may be sensitive to the estimation model and the event window specified. As such, we recalculate the CAR according to different specifications. For instance, we change the estimation window from 180-days to 90, 270 and 360 days. We also change the preevent window from 20 to 30 days. We find no material change in the results. We also repeat the sorted portfolio tests and compute CAR [0, +1] and CAR [0, +2]. The findings remain largely intact.

5. Concluding remarks

Extant literature almost unanimously concurs that the COVID-19 pandemic has brought about negative reactions to financial markets across the globe. Nevertheless, three interrelated issues have not been explored: market reactions during the subsequent recovery, industry heterogeneity and individual stocks' risk profile. Our study addresses these matters.

We use the COVID-19 pandemic situation to conduct an experiment-like study that focuses on stock market reactions under stress. Particularly, we analyze stock response to eight pandemic related news in 2020 across different industries comprising the S&P500 index. The findings show that the pandemic-induced reactions are not consistent across industries. Investors seem to factor in the potential impact of the news on underlying product markets. For instance, the immediate reactions to negative news are positive in one industry, negative in a few and mixed in others. On the other hand, the reactions to positive news are predominantly mixed in all industries except for the information technology and the consumer discretionary industries where the reactions are positive for the most part. The results are not materially different when examining several other Covid-19 related announcement dates.

We also find that low beta portfolios exhibited greater *abnormal* returns (in absolute value) than high beta portfolios during down markets while high beta portfolios exhibited greater abnormal returns (in absolute values) when the market started to recover. However, these findings do not hold when we examine the beta effect and industry effect jointly. Specifically, we find that beta does not seem to explain the abnormal returns reported in various industries during times of negative sentiment. During times of positive sentiment, both the beta effect and industry effect are present. This result implies that under stressful situations investors tend to be more concerned with industries' general conditions and give less considerations to individual stock risk profiles. In up markets, investors consider both individual stock characteristics as well as anticipated movements at the industry level.

Notes

1. We also consider several other dates of significant news related to the COVID-19 pandemic.
2. Of course, one can easily identify more dates. Nevertheless, we believe that the dates we have selected reflect the most significant pandemic related news.
3. Although it is called the S&P500, the index contains 505 stocks because five of its component companies have two share classes of stock.
4. Available at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
5. We thank an anonymous referee for this suggestion.

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