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Stock market in the age of COVID19: Mere acclimatization or Stockholm syndrome?

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ABSTRACT

We investigate the behavior of stock prices to variations in COVID19 infection rate over time. To study the inter-temporal impact of the pandemic on major stock indexes, we apply factor model, and disaggregate the sample period in three COVID19 waves. We bring interesting evidence on the so-called *immune* behavior of stock indexes. While no signs of stock market immunity to the disease were confirmed, the opportunities created by the pandemic would help new winners, causing a shift of sectoral gains. Distinguishing the surges from plunges in the COVID19 infections, we observe the behavior of stock indexes towards different scenarios during the pandemic. While the conventional wisdom may lead to an overall probable pessimistic outcome, we find that diversity and speedy adjustment based on new business models resulted in sizable theoretical inconsistencies and asymmetries in the response of stock indexes to the pandemic.

1. Introduction

The outbreak of COVID19 has divided the modern history of mankind into two quite distinct halves, and the coming years, if not decades, will remain marked by the consequences of the unprecedented spread of this pandemic. The SARS-Coronavirus pandemic has shaken the fabric of human life from all aspects, explicitly by the beginning of year 2020.¹ Where it caused death and disease, on one hand, it has also resulted into an upheaval in stock markets and has disrupted supply chains around the world, on the other. Outbreak of the virus is no doubt the worst shock of the current century, so far, that has challenged the health systems and has shaken the strongest of the world's economies. The pandemic, identified as due to new Coronavirus (severe acute respiratory syndrome Coronavirus 2, or SARS-CoV-2), and later renamed as Coronavirus Disease-19 or COVID19, by the World Health Organization (WHO), has caused severe initial damages to both life and kind. By the end of September 2021, there had been more than 200 million reported cases of COVID19 globally and over 4.5 million deaths (WHO, 2020). Global economy contracted by 3.5 percent in 2020 (IMF, 2020), which means a 7 percent net loss, for the growth forecast back in October 2019 was that of 3.4 percent expansion. Though the aftereffects of this pandemic are yet to be observed, the trajectory of consequent economic slowdown remains simple to understand.

Rapid spread of COVID19 was met by several public health measures adopted by governments across the globe (Mégarbane, Bourasset, & Scherrmann, 2021; O'Donnell, Shannon, & Sheehan, 2021). Such measures intended to prevent the pandemic spread, including social/physical distancing, business shutdowns, closure of educational institutions, restricted transport, prohibition of

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¹ The pandemic outbreak dates back to December 2019 in Wuhan province of China, however the immense spread and panic appeared 31 January onward, once the World Health Organization (WHO) announced Global Health Emergency.

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mass gatherings and the continual lock-downs, which, reportedly though, saved thousands of lives (Akhtaruzzaman, Boubaker, & Sensoy, 2021c; Mégarbane et al., 2021), resulted in sizable slowdown in economic activities. Where lock-downs reduced the retail sales, closure of international borders resulted into considerable disruption of the supply chains, thus further fueling the production downtrend, rising unemployment, and poverty thereof (Akhtaruzzaman, Boubaker, Chiah, & Zhong, 2021a; Coibion, Gorodnichenko, & Weber, 2020). Though real macroeconomic activity started suffering with a shorter lag, stock markets showed signs of panic right from the very start of the pandemic in the early 2020.

Stock markets are highly sensitive to news, and variations in stock prices quickly reflect all information concerning future events (Niederhoffer, 1971). According to Merrill (1984), "The market has some very bad moments immediately following the tragic news. Selling drives prices down to a surprising degree. However, when a day has passed, the market recovers from its panic, and sometimes works upward to a higher level". Thus the question that if *global events influence the stock market*, is not that difficult to answer. Among many other ups and downs in the stock markets, the Great Recession of 2008–09 also caused an initial sharp decline in stock prices, where mostly the panic lead the retail investors to sell their stock holdings. However, market also showed quick recovery once the institutional investors found undervaluation in some corners. Compared to the Great Recession, the COVID19 outbreak appeared as even bigger a surprise, and thus studying market trends during the pandemic, may clarify the sensitivity of stock prices to large and unexpected shocks.

On examining global stock markets, one observes that consequent upon the outbreak of the COVID19 pandemic, stock markets recorded an initial impact in the early 2020, followed by an equally stronger recovery within few months. Stock markets through variations in major stock indexes showed an indifference towards the spread, fatalities and socio-economic outcomes of COVID19, after March 2020. Subsequent to the price collapse of March 2020,² global capital markets showed a persistent recovery and recorded resistance to the pandemic (O'Donnell et al., 2021). The U.S. stock market indexes were not an exception during this time. Several explanations to this behavior have been tossed up so far: Rationality, central banks' reactions, stimulus packages, optimistic news on the vaccine preparation outcomes, immunity, and aggregation, among others. Whatever the reason be, sharp recovery of the U.S. stock markets and the persistent growth during the age of COVID19, pose important questions on the behavior of both value and growth investors. Therefore, in this study we attempt to investigate the U.S. stock markets' behavior during different phases of the current COVID19 pandemic.

This study contributes to the existing literature from three aspects: (i) Our sample period covers the first three COVID19 waves. Our work is different from (Akhtaruzzaman, Boubaker, Lucey, & Sensoy, 2021b) who divide the pandemic into two phases on the basis of fiscal and monetary stimuli timings. We are also different from (Yousfi, Zaied, Cheikh, Lahouel, & Bouzgarrou, 2021) who consider the first two waves of the pandemic for the U.S. and the China. We divide our sample into three waves, on the basis of variations in the COVID19 infection rate, using statistical approach for a clearer understanding of the market behavior during different phases of the pandemic. In this way, while we attempt to avoid the potential aggregation bias of large panels, our longer sample period allows us to better explore the earlier stock market decline met by equally sharp rise simultaneous to the pandemic spread. (ii) While the pandemic spreads and new variants have been showing up continually, significant variations have also been recorded in the growth of cases on daily basis. These variations could be classified as three non-mutually exclusive events: *no new cases*, *surge in cases*, and *decline in growth of new cases*. We investigate the reaction of major U.S. stock indexes towards these three different events separately. This approach is helpful in distinguishing reaction and the behavioral traits of retailers from the institutional investors. Besides, this may also lead to further explore the prevalence and duration of the potential negative and positive biases in the stock markets facing big news. (iii) Variations in the stock indexes are due to number of observable and unobservable factors. Where COVID19 supposedly be one, the impact of other factors cannot be ignored at the same time. As a latent factor model relies on the variations in stock indexes that occur on exogenously identified pandemic (event) days, we believe that the use of factor model suits this investigation. To see the clear picture, our factor model separates the COVID19 factors from the other macroeconomic factors.

Our results are in line with the existing literature on the pandemic and its effects on equity prices. We find that the initial response of stock markets was sudden, brutal and as per theoretical expectations — adverse to the outbreak and to the spread of the pandemic news. However, we are different from the existing studies as our disaggregated analysis of the response of stock indexes to three different waves brings important evidence on the behavior of stock markets and the players thereof. We find that though the stock indexes behave in a classical and textbook way to the Wave01, their behavior during the subsequent waves was characterized by serenity, stability and a continuous recovery. Such speedy adjustment and adaptation by the stock indexes to the '*new-norm*' may be due to three possible assumptions, among others: (1) the sectoral gains made by the new winners over-shadowed the loses of others, (2) it portrays an overall optimistic image of stock markets towards exogenous shocks, and (3) the behavioral rigidities of investors.

The rest of this paper is organized as follows: In Section 2, we review some of the prominent studies on the subject. Section 3 presents data and testing strategy. In Section 4, we record and discuss the results, while Section 5 concludes.

² Most stock indexes including S&P500 and Dow Jones showed their worst dip since Black Monday of 1987 (Stevens, Fitzgerald, & Imbert, 2020)

2. Brief literature review

There is a long-standing tradition in literature of assessing the impact of shocks on macroeconomic variables. The relationship between macroeconomic forces and stock prices has remained a subject of interest to the researchers, economists and financial analysts. As per (Challe & Giannitsarou, 2014) studying stock prices reaction to shocks are highly meaningful to understand the transmission channels of different policies, and also to bridge the gap between theory and practice. This is one reason ever-since the Keynesian concept of 'animal spirits' that a great strand of literature has been sacrificed to understand the determinants of savage fluctuations in and the behavior of stock markets.

Niederhoffer (1971) reports that news related to world event in media influenced the movements in stock markets. This was later confirmed by Cutler, Poterba, and Summers (1988), who figure out that one third of variance in stock prices was due to the news articles. However, this brings forward the question of lag, or the time, stock prices may take to react to news or to the world events. In this regard, Gallagher and Taylor (2002) find that the stock market response to changes in real economic activity was not immediate. However, one may argue that this relates to the type of shock facing the stock prices.

Among the relatively recent studies, Gupta, Inglesi-Lotz, et al. (2012) conclude that policy shocks were limited in their role in stock price variations, compared to the impact of "Great Recession" and its after effects. One may read this finding as, unexpected shocks cause higher uncertainty than the expected shocks and this supports our argument going forward, as the most recent and the unprecedented shock facing global stock markets is due to the outbreak of COVID19 pandemic. Where it was unexpected in the start, the temporal length of this shock may have given stock markets enough time to behave rationally.

With the COVID-19 pandemic, the first half of the year 2020 witnessed the emergence and exponential increase in the number of studies focusing on the impact of the pandemic and mobility restrictions, but also on monetary policy announcements and decisions on macroeconomic expectations. A first review of this literature can be found in Brodeur, Gray, Islam, and Bhuiyan (2020), who review some of the recent studies on the economic consequences of the pandemic and the policy reactions thereof. Among the initial attempts (Carlsson-Szlezak, Reeves, & Swartz, 2020) describe that COVID19 may impact the economies in three ways: consumer spending, financial markets and supply-side, and present a bleak economic outlook as a result of the pandemic. (Akhtaruzzaman, Boubaker, & Sensoy, 2021c) argue that the magnitude of the increase in these correlations is considerably higher for financial firms. Applying the DCC approach to examine contagion transmission for both financial and non-financial firms, they find that both financial and non-financial firms experience a significant increase in the conditional correlations between their stock returns.

Zhang, Hu, and Ji (2020) report dramatic impacts of the initial spread of COVID-19 on financial markets globally. They support that the pandemic outbreak lead to a significant increase in global financial market risk and causing investors to suffer significant losses initially over a short period of time. Market risk an uncertainty remains at epic in most studies on the COVID19 pandemic. Ashraf (2020) analyzes COVID19 infections and fatalities for a panel of 64 economies to examine the stock market responses to the crisis. He reports negative response of stock markets to the growth in the number of confirmed cases. Albuiescu (2021) using ordinary least squares (OLS) regression, examines the impact of official announcements of COVID-19 new cases and the fatality ratio on the volatility of the US financial market. He finds that the pandemic enhanced volatility of the S&P 500 index. In his study, Albuiescu suggests that the extended COVID19 pandemic could be an important source of financial volatility and thus a major challenge for risk management. However, the outcome of prolonged pandemic has been discussed differently by Carlsson-Szlezak et al. (2020), who, through the "shock geometry", describe optimistic U, V, as sharp recoveries and a possible L shaped recovery path as a worst case scenario.

In their study (Akhtaruzzaman, Boubaker, Lucey, et al., 2021b) examine the role of gold as a hedge or safe-haven asset during two different phases of the COVID19 pandemic crisis, where their phases correspond to the timing of fiscal and monetary stimuli. They find that though gold served as a safe-haven asset for stock markets during Phase I (December 31, 2019–March 16, 2020) of the pandemic, it lost its safe-haven role during Phase II (March 17 April 24, 2020). One can read interpret these results as a reflection of the asymmetric behavior of market during the different waves of the pandemic. On similar lines, Akhtaruzzaman, Boubaker, Chiah, et al. (2021a) study the oil price risk exposure of financial and non-financial industries during the COVID19 pandemic. They find that while oil supply industries benefit, the oil user industries and financial industries react negatively to positive oil price shocks, thus reflecting the moderation in the oil price risk exposure during the pandemic.

While literature is very recent and studies are coming up with a significant flow, most of the existing work is focused on the stock price volatility and the Uncertainty-COVID19 nexus. We contribute to the existing literature by disaggregating the sample period into three major waves to study the stock prices' behavior during the pandemic, yet at different stages. In this regard, going further, we separate the *surges* in COVID19 cases from *plunges* for a better understanding of this behavior and to figure out any inconsistencies or asymmetries thereof. We apply factor model to understand the degree by which variations in COVID19 infection rate could be held responsible for the variations in stock prices.

3. Data and empirical strategy

3.1. Data

Whereas most existing studies on the subject apply panel analysis, one obvious reason behind the use of panel data is the lack of sufficient observations (Salisu, Ebu, & Usman, 2020). However, as we have now enough data to conduct an in-depth time series analysis, we use daily data on four major stock indexes for the US economy for the period 21 Jan 2020 to 6 May 2021. The selection of stock indexes is based on their coverage and composition to study the reaction of stock market in a comprehensive manner. It is a

fact that these stock indexes are highly correlated over the long-run, however, we are more interested in the short-run variations on the basis of their composition to study the behavior of different investor during different phases of the turbulent times. Therefore, this study focuses on the United States, being the single most affected economy in terms of contagion and fatalities till this moment.³ We collect daily data on four stock market indexes including, S&P500, Wilshire5000, Dow Jones, and NASDAQ on one side and on the number of COVID19 positive infections on the other. Where the S&P 500 Index represents approximately 80% of the total value of the U.S. stock market and gives a good indication of movements in the U.S. market as a whole,⁴ the Dow Jones (DJ) industrial average represents about a quarter value of the entire U.S. stock market and is known for its listing of the best blue-chip companies.

The Wilshire 5000, which is also known as the *total market index*, represents the entire U.S. stock market.⁵ However, the NASDAQ Composite Index is known for being heavily tech-weighted. This index includes several sub-sectors across the tech-market including software, semi-conductors, bio-tech, and also, unlike the Dow Jones and the S&P 500, it also includes many speculative companies with small market capitalization.⁶

Starting date for the data selection is same for the first registered COVID19 case in the United States.⁷ Determination of start and end of waves is a trivial exercise. One solution could be to visually and graphically observe and detect the troughs and crests in the COVID19 cases to tag the existing waves in the pandemic spread. One may also identify the waves on the basis of Variants of Concern (VoC).⁸ However, scientifically this could also be done using different statistical methods including Z-score and filtering, among others. In this study, we use Wavelet analysis of variance for this purpose. In addition, we also apply Bilen-Huzurbazar Outlier Detection process to confirm the waves determined using variance decomposition of wavelets.⁹

In this regard, we record our Wave01 from January 01, 2020 to June 12, 2020 containing more than one hundred observations. Wave02 starts on June 15, 2020 ending on September 04, 2020, with less than a hundred observations. Finally, Wave03 covers the period September 7, 2020 onward till the beginning of May 2021 with above two hundred observations.¹⁰ We do not consider the period after May 2021, due to the consistency in stock indexes' growth, despite growing concerns on a potential fourth wave of COVID19.

Where a lot is still expected to be done, conventionally most existing studies on COVID19 and its macroeconomic impacts consider penal data for many countries (Ashraf, 2020; Salisu et al., 2020). However, the impacts of the pandemic are not the same across different economies, at least the intensity of infection spread and fatalities has so far been observed inconsistent and with different lags. Similarly, the differences in the economic structures of different countries in the panel also makes it challenging to study with caution the fixed or random effects. This observation guides us towards the assumption that a disaggregated analysis may lead to new and important findings.

Table 1 reveals that while overall trends of the four indexes remained somewhat immune to the pandemic, a disaggregated look into the indexes during three infection waves reflect a different scenario. One may observe that stock indexes responded to the initial shock in consistency with the efficient market hypothesis, however, the recovery was quick and the behavior of stock indexes in the last two waves reflect a clear mitigation of the pandemic affects.

Further inquiry leads to a separation of rising infection days from those where we record a decrease in infection (see Table 2). Simple look into the number of surges and plunges in the COVID19 infection compared to the same for stock indexes confirms the earlier findings.

3.1.1. Empirical strategy

Stock market trends being leading macroeconomic indicators, are highly sensitive to various firm-specific and external factors. One way of analyzing the existing and potential trends in stock markets is to study the behavior of composite stock indexes. As these indexes are composed of stock prices of different corporations, fundamental factors have a key role in the determination and volatility of stock prices and thus of stock indexes. However, the importance of external factors cannot be denied. These factors include technical factors, macroeconomics environment, innovations, market sentiment and news. Most of the time, the external factors are exogenous to the fundamentals and affect stock prices through their influence on the internal factors including earning base and valuation multiple. These factors are therefore our main idiosyncratic factors having an impact on the stock prices and on the returns thereof.

In a typical factorial environment, both common and idiosyncratic factors impact the stock markets, however, as we focus on a large yet single market with different composite indexes for the same economy, the scope factors are the idiosyncratic in our case. These idiosyncratic factors are latent and sometimes unobserved. One interesting contrast between observed and unobserved latent variable is that the latter is free of random or systematic errors, however these can only be indirectly measured. For instance, where news are abstract latent concepts, COVID19 infection rate, change in fatalities and variation in retail sales are less abstract and directly measurable. Here one assumption is notable that stock prices respond to the unexpected change in the COVID19 spread or

³ The study cover the period till May 2021.

⁴ S&P Dow Jones Indices. "Dow Jones Industrial Average". <https://www.spglobal.com/spdji/en/indices/equity/dow-jones-industrial-average/#overview>

⁵ Wilshire. "Wilshire 5000 Total Market Index Fact Sheet.

⁶ <https://www.nasdaq.com/market-activity/index/comp>

⁷ The U.S. confirmed its first Coronavirus case on the 21 January 2020 - <https://www.cdc.gov/media/releases/2020/p0121-novel-coronavirus-travel-case.html>

⁸ <https://www.who.int/en/activities/tracking-SARS-CoV-2-variants/>

⁹ The details can be obtained from the corresponding author on request.

¹⁰ Total number of observations considered during estimations may slightly differ from these numbers due to the multiple iterations and possible removal of outliers.

Table 1
Descriptive statistics for complete and for disaggregated samples.

		Mean	Median	Max.	Min.	Std. Dev.	St. Er	Skewness	Obs.
Full term	Dow Jones	0.07	0.11	11.37	-12.93	2.07	(0.04)	-0.52	327
	NASDAQ	0.14	0.28	9.35	-12.32	2.08	(0.03)	-0.68	327
	S&P 500	0.09	0.17	9.38	-11.98	1.96	(0)	-0.59	327
	Wilshire 5k	0.09	0.17	9.40	-12.29	1.98	(0.01)	-0.72	327
	Cases	6.83	1.28	225.11	0.00	23.03	(0.06)	6.59	326
	Deaths	5.43	0.78	300.00	0.00	21.63	(0.06)	9.44	315
Wave 01	Dow Jones	-0.07	0.00	11.37	-12.93	3.40	(0.07)	-0.24	103
	NASDAQ	0.07	0.20	9.35	-12.32	3.10	(0.03)	-0.49	103
	S&P 500	-0.04	0.03	9.38	-11.98	3.16	(0.06)	-0.29	103
	Wilshire 5k	-0.04	0.06	9.40	-12.29	3.19	(0.07)	-0.39	103
	Cases	19.12	4.58	225.11	0.00	38.50	(0.09)	3.57	102
	Deaths	17.01	3.93	300.00	0.00	37.96	(0.08)	5.18	91
Wave 02	Dow Jones	0.16	0.33	2.32	-2.84	1.09	(0.12)	-0.68	60
	NASDAQ	0.28	0.56	2.51	-4.96	1.34	(0.11)	-1.32	60
	S&P 500	0.20	0.35	1.90	-3.51	1.01	(0.12)	-1.31	60
	Wilshire 5k	0.21	0.33	1.90	-3.56	1.04	(0.12)	-1.25	60
	Cases	1.87	1.69	5.55	0.66	1.18	(0)	1.64	60
	Deaths	0.82	0.71	2.45	0.47	0.34	(0)	2.50	60
Wave 03	Dow Jones	0.12	0.12	2.95	-3.43	0.95	(0.02)	-0.34	163
	NASDAQ	0.13	0.14	3.85	-4.11	1.40	(0.08)	-0.33	163
	S&P 500	0.12	0.07	2.38	-3.53	1.02	(0.04)	-0.51	163
	Wilshire 5k	0.14	0.11	2.46	-3.44	1.04	(0.04)	-0.49	163
	Cases	1.00	0.75	4.40	0.18	0.88	(0.03)	1.92	164
	Deaths	0.68	0.57	2.09	0.14	0.40	(0.02)	0.98	164

¹The numbers show the descriptive statistics based on the growth rates in the respective variables.

²Wave01: January 01, 2020 to June 12, 2020. Wave02: June 15, 2020 to September 04, 2020. Wave03: September 7, 2020 to May 06, 2021.

³Author's calculations - Source: Thompson Reuters.

Table 2
Variations in stock indexes, COVID19 cases & fatalities.

		Dow Jones	NASDAQ	S&P 500	Wilshire 5k	Cases	Deaths
Full term	+	160	164	157	163	179	147
	-	167	163	170	164	124	180
	<i>Total</i>	<i>327</i>	<i>327</i>	<i>327</i>	<i>327</i>	<i>303</i>	<i>327</i>
Wave 01	+	53	51	51	50	45	38
	-	50	52	52	53	34	65
	<i>Total</i>	<i>103</i>	<i>103</i>	<i>103</i>	<i>103</i>	<i>79</i>	<i>103</i>
Wave 02	+	34	31	31	31	41	26
	-	26	29	29	29	19	34
	<i>Total</i>	<i>60</i>	<i>60</i>	<i>60</i>	<i>60</i>	<i>60</i>	<i>60</i>
Wave 03	+	83	82	75	81	93	83
	-	81	82	89	83	71	81
	<i>Total</i>	<i>164</i>	<i>164</i>	<i>164</i>	<i>164</i>	<i>164</i>	<i>164</i>

¹Here the '+' and '-' signs represent the increase (surges) and decrease (plunges) in the growth of returns in the respective stock indexes, respectively.

²Wave01: January 01, 2020 to June 12, 2020. Wave02: June 15, 2020 to September 04, 2020. Wave03: September 7, 2020 to May 06, 2021.

³Author's calculations - Source: Thompson Reuters.

to some unexpected variation in the macroeconomic environment. For, if these changes are the expected ones then the market is supposed to be, *a priori*, attuned to it. As the latent factor model depends mainly on the variations in stock prices due to exogenous factors, it better serves the purpose of this study. Such unobserved factor models have recently gained attention of researchers in macroeconomics, particularly for the short-run analysis¹¹ (Rigobon & Sack, 2004).

¹¹ Another way to roughly observe the variation and the patterns thereof, is to look into the variance, covariance and correlation statistics of the series. One can see in the appendix Table A.1, which advocates the choice of a factor model for this investigation.

Therefore, we proceed with a linear simultaneous equations setup to develop our estimation strategy as follows¹²:

$$bsp_t = ax_t + d\varepsilon_t \quad (3.1)$$

Simplifying Eq. (3.1) we get:

$$sp_t = b^{-1}ax_t + b^{-1}d\varepsilon_t \quad (3.2)$$

Here sp is a vector of demeaned endogenous changes in stock indexes. In a linear environment as per Eq. (3.2), variations in stock indexes depend on certain common and idiosyncratic factors (x_t and ε_t). Here x_t could be macroeconomic conditions, policy announcements, currency market dynamics and oil price changes, etc., that are common to all sp s. Here COV_t are the different changes in the COVID19 infection rate at time t ; while $f_{k,t}$ are unobservable exogenous and non-COVID19 factors. COVID19 infection rate remains random (see Table 2) and we record both positive and negative growths in a stochastic manner. Though, in the early days of the outbreak of the pandemic we also observe no-change days of the infection, based on the fact that infection testing was limited, we ignore these non-COVID19 days to minimize the data reporting errors.

We rewrite Eq. (3.2) in reduced form by separating the unobservables by identifying the pandemic spread shocks as $COV_t = \varepsilon_t$ and unidentified exogenous factors¹³ as $f_1 \dots f_k$ in the following form:

$$sp_t = \alpha COV_t + \sum_k \beta_k f_{k,t} \quad (3.3)$$

Whereas, the Efficient Market Hypothesis supports rational behavior of stock markets, considering all relevant information in an unbiased way, others argue that stock prices were instead driven by human psychology. Most people overreact to shocks and unexpected news and thus affecting stock prices and the market thereof; it is driven by emotions rather than purely economic fundamentals (De Bondt & Thaler, 1985). Further, research in human Psychology indicates that human reactions may contain a negativity bias (Rozin & Royzman, 2001), which means that people may overreact to the bad unexpected news, than to the good ones. This motivates us to incorporate both the increases and decreases in the COVID19 infection rate separately in our model. However, it will be misleading to assume the pandemic being the only determining factor towards any change in the market behavior, as various other idiosyncratic factors also affect the markets. Therefore, to weed out the effects of such underlying factors, our factor model follows the methodology proposed by Rigobon and Sack (2004).

$$sp_t = \alpha COV_t^{surge} + \beta COV_t^{plunge} + \sum_k \gamma_k f_{k,t} \quad (3.4)$$

Eq. (3.4) separates the rising infection days from those where we record a decrease in the infection rate, keeping the non-COVID19 factors apart. By construction both the negative and positive infection growths are mutually exclusive processes with unit variance. In what follows, we classify observations into three possible sub-periods based on the infection rate variations. Here α , β , and γ are the factor loadings, where α captures the change in stock indexes due to one standard deviation unexpected rise in COVID19 infections.

$$\begin{aligned} Esp_t sp'_t &= \alpha\alpha' + \sum_k \gamma_k \gamma'_k; \quad (\text{Infection Surge Days}) \\ Esp_t sp'_t &= \beta\beta' + \sum_k \gamma_k \gamma'_k; \quad (\text{Infection Plunge Days}) \\ Esp_t sp'_t &= \sum_k \gamma_k \gamma'_k; \quad (\text{No-Change Days}) \end{aligned} \quad (3.5)$$

In Eq. (3.5) time t represents the segment of sample period respective to the COVID19 spread conditions.

3.1.2. Baseline factor model

While the infection related events could be easily divided into three sets of possible outcomes as discussed earlier,¹⁴ the number of other factors (non-COVID19) is indeterminate, except that there must be at least as many of those factors as the number of indexes considered in the sample $N \geq n$, since the rank of covariance matrix of sp on idiosyncratic factors is n , which gives $\sum_k \gamma_k \gamma'_k = \text{rank}(Esp_t sp'_t | t \in NC)$. Thereby, to simplify we rewrite Eq. (3.5) as a linear function of pandemic and a weighted sum of non-COVID19 factors as follows:

$$sp_t = \alpha COV_t^{Surge} + \beta COV_t^{Plunge} + \xi_t \quad (3.6)$$

Here sp_t refers to the vector of stock returns at time t , COV_t^{Surge} & COV_t^{Plunge} are the positive and negative variations in the COVID19 infection rate, respectively.¹⁵ α , and β are the factor loadings. ξ_t represents all the non-COVID19 factors affecting stock indexes and it has the same time series properties as that of structural shocks in structural vector autoregression models. As per

¹² Besides many others this approach has been applied by Claus and Nguyen (2020), Dai and Singleton (2000), SYED (2021), Craine and Martin (2008) and Diebold, Rudebusch, and Aruoba (2006).

¹³ As per scope of this study, we do not separate the unidentified factors. Here $f_{n-1} = x_1, f_n = x_2 \dots$

¹⁴ No-Change, Surge, Plunge in cases.

¹⁵ Positive variation here refers to an increase in number of infections.

scope of this study our interest centers mainly around the COVID19 factors. However, it may bring further evidence to separate the impact of each non-COVID19 factor and to assess their impact on stock market in a parsimonious setup.

In wide sense:¹⁶

$$\begin{aligned} \xi_t & \sim (0, \Pi) \text{ For all } t \\ m_t^{Surge} & \sim (0, 1) \text{ For Surge Day, } 0 \text{ otherwise} \\ m_t^{Plunge} & \sim (0, 1) \text{ For Plunge Day, } 0 \text{ otherwise} \end{aligned} \tag{3.7}$$

Considering the sum of non-COVID19 factors' effect as $\xi = \sum_k^n \gamma_k f_k$, the variance–covariance matrix can be identified as:

$$\Pi = E [\xi \xi'] = \sum_k^{N \geq n} \gamma_k \gamma_k' \quad (\text{where } \lambda_{ij} \in \Pi)$$

In this way, we can summarize the model on second moments as follows:

$$\begin{aligned} Esp_t s p_t' &= \alpha \alpha' + \Pi; & \text{for Surge Days} \\ Esp_t s p_t' &= \beta \beta' + \Pi; & \text{for Plunge Days} \end{aligned} \tag{3.8}$$

3.1.3. Estimation method

Generalized Method of Moments (GMM), a framework described by Hansen (1982), appears to be naturally the best suited method to estimate Eq. (3.8). To make observable sample moments the closer possible to the implied theoretical moments of the model, GMM has a better selection of the model parameters, where GMM estimates are normally distributed as per standard regularity conditions, see Hamilton (1994). Thus, similar to Eq. (3.5) we get the following GMM moment conditions for our model, purposefully ignoring the non-COVID19 days:

$$\begin{aligned} V_{ijt \in E^{Surge}}^{Surge} &= y_{it \in E^{Surge}} y_{jt \in E^{Surge}} - (\alpha_i \alpha_j + \lambda_{ij}) \\ V_{ijt \in E^{Plunge}}^{Plunge} &= y_{it \in E^{Plunge}} y_{jt \in E^{Plunge}} - (\beta_i \beta_j + \lambda_{ij}) \end{aligned} \tag{3.9}$$

Eq. (3.9) shows the two schemes where each has $n(n+1)/2$ elements stacked into respective vectors: $V_t^{Expansion}; V_t^{Contraction}$.

In this way the GMM estimates of the unknown parameters $\Psi_z = \{\alpha_i^{Surge}, \beta_i^{Plunge}, \Pi\}$ minimize the following loss function.

$$\min_{\Psi} L(\Psi_z) = Z(\alpha^{Surge}, \beta^{Plunge}, \gamma)' H^{-1} Z(\alpha^{Surge}, \beta^{Plunge}, \gamma) \tag{3.10}$$

Where $\Psi_z = (\alpha^{Surge}, \beta^{Plunge}, \gamma)$, and γ is a diagonal matrix of factor loadings on non-COVID19 factors.

It is worth noting here that when the number of moment functions surfeits the number of unknown parameters the model is over-identified, and it is usually not possible to set the sample average of these moment functions exactly equal to zero. We follow the solution proposed by Hansen (1982), to set a linear combination of the sample average of the moment functions equal to zero, with the dimension of the linear combination equal to the number of unknown parameters (Imbens, 1997).

4. Results & discussion

Theoretically a negative economic shock should exert downward pressure on stock prices, thus leading the stock indexes towards a declining trend, while a positive shock may result in the opposite. Such a reaction could be due to macroeconomic demand or supply shocks, as it has been reported widely by researchers in the context of COVID19 (Ashraf, 2020; Gupta et al., 2012; Huang & Guo, 2008; Salisu et al., 2020). While our findings are partly inline with the theoretical macroeconomic framework, we record interesting and inconsistent findings as well.

4.1. Aggregate sample period

In Table 3 we report results for the complete sample period as well as for the disaggregated period in three waves. Our point of interest is the direction and magnitude of factor loadings on positive and negative changes in COVID19 infection rates. The results for the overall sample period indicate that both COVID and non-COVID factors contribute significantly to the volatility in the stock prices and the stock indexes in turn. We find that stock indexes during this period emit mixed signal. With the exception of S&P500, all the other three stock indexes exhibit pessimistic behavior during both surge and plunge days of COVID19 infection rate. The tech-dominated NASDAQ and Dow Jones exhibit similar behavior and reflect an overall pessimistic reaction towards both surges and plunges in the infection rate. S&P shows slightly different behavior than the other stock indexes. We find that S&P behaves in accordance to the theoretical macroeconomic fundamentals. This stock index follows the infection trend and where growing pandemic discourages buying behavior, during the plunge days, we record positive movements in the S&P-500 index. Wilshire-5000 stays distinct in its behavior from all the other indexes. It shows, though weakly significant, a rise during the days when infection rate decreases. However, interestingly it moves up along the infection trend during the high spread days. Such a diversified, partially inconsistent and asymmetric behavior supports our argument of a disaggregated analysis and therefore, in the following section we disaggregate our sample period in three waves.¹⁷

¹⁶ Wide sense distribution refers to constant variance and zero mean.

¹⁷ As a robustness check, we also conduct a Robust Least Square Analysis for the full sample and the three waves. We find no anomalies in the results and the robustness check confirms the sanctity of our factor model findings — see Table A.2 in the appendix.

Table 3
Results based on factor model.

		Dow Jones		NASDAQ		S&P 500		Wilshire 5k	
		F. Loading	St. Er	F. Loading	St. Er	F. Loading	St. Er	F. Loading	St. Er
Full sample	α	-0.81**	0.31	-0.54**	0.14	-0.35**	0.08	0.65**	0.22
	β	0.15**	0.06	0.46**	0.16	-0.05**	0.02	-0.92*	0.46
	γ	-0.11**	0.05	-0.32**	0.09	-0.24**	0.05	-0.21**	0.04
Wave-01	α	-0.24**	0.05	-0.01*	0.00	-0.19*	0.10	-0.31*	0.10
	β	-0.42*	0.21	0.35**	0.15	0.12**	0.04	0.57	1.14
	γ	-0.61	1.02	-0.41**	0.16	-0.54*	0.27	-0.79**	0.15
Wave-02	α	0.01**	0.00	0.06**	0.01	0.19*	0.10	0.22	0.49
	β	-0.03**	0.01	-0.04	0.03	-0.01*	0.01	0.17*	0.09
	γ	0.12*	0.06	0.35	0.27	0.45*	0.22	0.61**	0.11
Wave-03	α	0.54**	0.15	0.21**	0.04	0.45**	0.12	0.35**	0.08
	β	-0.65*	0.32	-0.22*	0.11	-0.06**	0.02	-0.31	0.54
	γ	0.87**	0.32	0.57*	0.29	0.97**	0.18	0.69**	0.10

¹ α , β - Surge, Plunge in COVID19 infection rate respectively and γ - Factors other than COVID19.

²F. Loading - Factor loadings. St. Er. - Standard Error.

³Level of significance: * represents 5%; ** represent 10%.

⁴Wave01: January 01, 2020 to June 12, 2020. Wave02: June 15, 2020 to September 04, 2020. Wave03: September 7, 2020 to May 06, 2021.

⁵Author's calculations - Source: Thompson Reuters.

4.2. Temporally disaggregated sample

4.2.1. Wave-01

Wave-01 covers the initial period when the global economies realized the existence of Coronavirus.¹⁸ This realization resulted in a global economic shock driven by travel restrictions, borders closures, and lock-downs. While these unprecedented measures impacted the global economies by and large, the stock markets were not an exception. All the stock indexes, in this study, record brutal variations during the first wave of the pandemic.

Our four stock indexes show a decline facing a rising infection rate and the news thereof. Separation of negative from positive growths in the pandemic proves effective and we record that with the exception of Dow Jones, all the stock indexes show pessimistic behavior even when the infections rates decline. During the Wave-01, which could be named as the panic-wave, uncertainty remained at its peak, and all sectors recorded rapid and large declines. During the days of decrease in infection rate, though we have inconclusive result for Wilshire 5000 index, NASDAQ reveals strong negative behavior compared to the S&P 500. Overall the first wave of COVID infection reveals a bleak picture of the US stock market and this confirms the efficient market hypothesis to greater extent. We also record that non-COVID factors played rather an important role in the significant variations recorded by all the stock indexes. Factor loadings on the non-COVID factors reveal that these factors outweighed the COVID19 effects. However, one may link these non-COVID factors being endogenous to the pandemic effects (see Table 3).

While during this wave, sectors like air and travel, aerospace, banking, insurance, hospitality industry and oil and gas among others, suffered significantly, certain sector began responding to the record stimulus packages and as a result we observe that despite a second assault by the COVID19, some sectors including pharmaceuticals, biotechnology, electronic social media, wholesale, and retail platforms record market-capitalization gains.¹⁹

4.2.2. Wave-02

The tide that took a turn after the mid-March 2020, due to the government's reaction in the shape of stimulus package, accompanied by the positive news on the potential vaccine and possible curative medicine, led some sectors regain their market losses.²⁰ In Table 3 we observe that the second wave is characterized by serenity and widespread stability compared to the earlier response of stock indexes to the pandemic shock. The inconsistencies seen during the first wave though continue, with a directional shift. Where during the Wave-01, stock indexes responded negatively to both rise and decrease in the COVID19 cases, in the second Wave the response of stock indexes, in general, remained positive to both positive and negative changes in COVID19 infection rate. We do not record any significant variations in terms of magnitude of the effect among different indexes.

One may find an important observation that the impact of non-COVID19 factor either remain mitigated or inconclusive during this wave. Though this short-lived second wave left the U.S. with smaller number of fatalities compared to the first wave, the pandemic spread recorded an exponential surge. While the significant increase in number of new cases, may factually be due to the increased testing and reporting, the sectoral recoveries, over the same time, put the stock markets back on track. New business models in

¹⁸ World Health Organization (WHO) declared COVID19 a pandemic on March 11, 2020.

¹⁹ ZOOM video teleconferencing software program, (by Zoom Video Communications) gained an additional market value of \$93 billion during the year 2020. Source: Thompson Reuters.

²⁰ On March 17, University of Minnesota begins testing Hydroxychloroquine, while at the same time administration asks Congress to send direct financial relief to the Americans. By the end of March 2020, Federal Drug Authority (FDA) authorizes Use of Hydroxychloroquine.

hospitality industry, health care and fitness, technology giants, including North America Tech.²¹ bounced back, thus outperforming the lagging sectors.²² Our results for the second wave are inline with the widespread optimism in the U.S. stock market in the face of an exponentially spreading pandemic.

4.2.3. Wave-03

As Wave-03 comprises of most of the observation in the sample, one may expect the results in this section to be inline with or at least influencing the results for our complete sample period. However, this is not the case and we find that stock markets record an acceleration beyond the stability earned during Wave-02. Results during the Wave-03 confirm the subsequent shifts from uncertainty to sanity and from sanity to recovery. However, we still record the inconsistencies in terms of stock indexes responses to the increases in COVID19 cases. All our four stock indexes show clear signs of back-on-track despite the high intensity of pandemic during this particular wave.

One may attribute the stability to the use of tele-medicine, education, partial removal of lock-downs, online shopping and distance-working. Online education, shopping and work, though not new phenomena, intensified during this period. The increased remote activities, and the launch of vaccine distribution, while brought hope of bringing life back to normal, resulted into new winners in the stock market. This is one reason, we record that despite surge in the number of new COVID19 cases, stock market shows a noticeable *immunity*. This particular result provides rough answers to the question of the coming COVID19 waves and their potential impact on the stock indexes. While population at large are still far from herd-immunity, stock markets seem acquired it through the non-COVID19 factors, indirectly supported by the pandemic.

Overall findings of the three COVID19 waves describe the chronology of a weakening dependence between infection rate and stock returns. In consensus with the existing literature on the subject, we can now confirm the adverse impact of the COVID19 pandemic on the US stock market (Akhtaruzzaman, Boubaker, Chiah, et al., 2021a; Akhtaruzzaman, Boubaker, Lucey, et al., 2021b; Yousfi et al., 2021). The initial lock-downs, closure of borders, and travel restrictions, caused to suffer various sectors including travel, tourism, banking, insurance, oil, and gas. However, stock indexes started revealing signs of confidence by the very beginning of the Wave02. Unlike (Yousfi et al., 2021) we find stability in the stock returns during the Wave02, which could greatly be attributed to the ease in lock-downs, stimulus packages (Akhtaruzzaman, Boubaker, Lucey, et al., 2021b) and to the introduction of new business models in hospitality industry, health care and education among others. The results of Wave03 ratify the correction observed during the Wave02 and confirm the recovery in the US stock markets, despite theoretically inconsistent co-movement between the infection rate and stock returns. Not just acclimatization but temporal adaptation to the pandemic by different sectors, particularly through tele-medicine, online shopping, remote learning and working are some of the recovery factors.

5. Conclusion

For those who have doubts that crises, while make some suffer, always bring opportunities and are blessings in disguise for others, may find a counter-evidence in the shape of the COVID19 pandemic and the financial impacts thereof. We explore the behavior of four prominent U.S. stock indexes facing COVID19 pandemic. Though the subject has been under tremendous research from different angles and aspects, we take the lead on disaggregation. In line, with the results of existing studies, we confirm that the impact of COVID19 pandemic was adverse and severe on the equity prices. However, as our study period is lengthier than most of the existing studies, our results negate the inverse conjunction of stock indexes and pandemic growth. Our results point towards inconsistencies as the pandemic grows, spreads and behaves in different waves. Stock indexes show a significant shift and an outright change in their behavior towards growing COVID19 cases. Apart from the first wave a noticeable improvement and recovery in the stock prices despite the increased COVID19 cases show the presence of asymmetric inconsistencies backed by behavioral rigidities in the trading corridors. Where the Wave01 shows a collapse of stock prices, Wave02 show stability and onward during the third wave we record a relatively stable recovery backed by the gains of new winners.

The sanity and stability of stock markets beyond mid-March 2020, on one hand may reflect heterogeneity in the construction of the stock indexes, reveal the speedy adjustment of stock market players in their apprehension of the future course of the economies at large, on the other. Our results may interest not only the retail and institutional investors, but the policymakers and researchers as well. The flexibility and the shock absorption capacity of the market indicates the underlying rationality that resulted into a comeback with greater pace after an initial collapse of the stock markets facing a global pandemic. In this way, though the COVID19 pandemic has placed question marks on the health systems across the board, it points towards zero sum behavior of stock prices during the turbulent times. As the COVID19 pandemic is yet to find an end, we believe that further studies will update these preliminary estimates. In this regard, an industry-level disaggregated analysis may shed more light on the asymmetric behavior of stock market to different waves of the pandemic.

²¹ Corporate Performance Analytics.

²² banking industry among others.

Table A.1
Covariance & correlation matrices.

		S&P 500		Wilshire 5k		NASDAQ		Dow Jones			
Covariance	Full	Cases	-7.10	(-3.24)	-7.57	(-3.41)	-5.84	(-2.49)	-7.31	(-3.15)	
		Deaths	1.05	(0.43)	0.62	(0.25)	1.84	(0.72)	1.43	(0.56)	
	Wave 1	Cases	-22.63	(-1.9)	-24.13	(-2.01)	-19.25	(-1.64)	-23.14	(-1.81)	
		Deaths	5.74	(0.43)	4.41	(0.33)	7.57	(0.58)	7.35	(0.51)	
	Wave 2	Cases	0.29	(1.77)	0.22	(1.43)	0.24	(1.57)	0.32	(1.62)	
		Deaths	0.11	(2.41)	0.09	(2.09)	0.10	(2.34)	0.12	(2.08)	
	Wave 3	Cases	0.06	(0.61)	0.06	(0.97)	0.04	(0.57)	0.06	(0.82)	
		Deaths	0.04	(0.82)	0.01	(0.47)	0.02	(0.52)	0.03	(0.77)	
	Correlation	Full	Cases	-0.18	(-3.24)	-0.19	(-3.41)	-0.14	(-2.49)	-0.18	(-3.15)
			Deaths	0.02	(0.43)	0.01	(0.25)	0.04	(0.72)	0.03	(0.56)
		Wave-1	Cases	-0.20	(-1.9)	-0.21	(-2.01)	-0.17	(-1.64)	-0.19	(-1.81)
			Deaths	0.05	(0.43)	0.03	(0.33)	0.06	(0.58)	0.05	(0.51)
Wave-2		Cases	0.23	(1.77)	0.18	(1.43)	0.20	(1.57)	0.21	(1.62)	
		Deaths	0.30	(2.41)	0.26	(2.09)	0.29	(2.34)	0.26	(2.08)	
Wave-3		Cases	0.05	(0.61)	0.08	(0.97)	0.04	(0.57)	0.06	(0.82)	
		Deaths	0.06	(0.82)	0.04	(0.47)	0.04	(0.52)	0.06	(0.77)	

¹Standard errors in parentheses.

²Author's calculations - Source: Thompson Reuters.

Table A.2
Robust least square estimation results.

		Dow Jones	NASDAQ	S&P 500	Wilshire 5k
Full sample period	Coefficient	-0.015**	-0.01**	-0.02**	-0.02**
	z-Statistic	(-62.21)	(-59.32)	(-28.33)	(-28.85)
Wave - 01	Coefficient	-0.016**	-0.013**	-0.02**	-0.02**
	z-Statistic	(-29.59)	(-20.19)	(-74.63)	(-68.23)
Wave - 02	Coefficient	0.175**	0.28**	0.16**	0.19**
	z-Statistic	(11.13)	(181.42)	(13.3)	(21.86)
Wave - 03	Coefficient	0.063**	0.05**	0.04**	0.06**
	z-Statistic	(12.69)	(22.32)	(11.1)	(11.91)

¹ α - Surge in COVID19 infection rate; β - Plunge in COVID19 infection rate and γ - Factors other than COVID19.

²Level of significance: * represents 5%; ** represent 10%.

³Author's calculations - Source: Thompson Reuters.

CRedit authorship contribution statement

Sarfraz Ali Shah Syed: Conceptualization, Methodology, Data curation, Writing – original draft preparation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Covariance - correlation analysis

Appendix B. Robustness

While the initial days of the outbreak, we record significant fluctuations in both the COVID19 cases and in the stock indexes. The sensitivity of most empirical methods to these outlier observations can result in coefficient estimates that do not accurately

reflect the underlying statistical relationship. Therefore, we apply robust least squares (RLS) method to our sample as a check on our results. RLS is designed to be robust, or less sensitive, to outliers. We report the RLS based results in Table A.2 in appendix. The results support our factor model findings, and one can read that while most fluctuations and variation in the stock indexes belong to the first wave, overall sample seems overwhelmed by the results of mere the first wave. However, during the second and third waves all the stock indexes show acclimatizing behavior in the face of rising infection rate.

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