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Modeling and analysis of the effect of COVID-19 on the stock price: V and L-shape recovery

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ABSTRACT

The emergence of the COVID-19 pandemic, a new and novel risk factor, leads to the stock price crash due to the investors’ rapid and synchronous sell-off. However, within a short period, the quality sectors start recovering from the bottom. A stock price model has been developed to capture the price dynamics during shock and recovery phases of such crisis. The main variable and parameter of the model are the net fund flow ($\Psi_t$) due to institutional investors, and financial antifragility ($\phi$) of a company, respectively. We assume that during the crash, the stock price fall is independent of the $\phi$. We study the effects of shock length ($T_S$) and $\phi$ on the stock price during the crisis period using the $\Psi_t$ obtained from both the synthetic fund flow data and real fund flow data. We observed that the possibility of recovery of stock with $\phi > 0$, termed as quality stock, decreases with an increase in $T_S$ beyond a specific period. A quality stock with higher $\phi$ shows V-shape recovery and outperform others. The $T_S$ and recovery period of quality stock are almost equal in the Indian market. Financially stressed stocks, i.e., the stocks with $\phi < 0$, show L-shape recovery during the pandemic. The stock data and model analysis show that the investors, in the uncertainty like COVID-19, invest in the quality stocks to restructure their portfolio to reduce the risk. The study may help the investors to make the right investment decision during a crisis.

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1. Introduction

The impact of a pandemic on the environment, economy, employment, stock market and many other sectors is severe [1–4]. A number of pandemics, which happened in 1918–1919, 1957–1958 and 1968, affected the economy and stock markets worldwide badly [5–7]. The pandemic’s effect, the coronavirus disease (COVID-19), maybe more severe on the economy and stock market, including many other sectors, due to its contagion nature [7–9]. The COVID-19 leads to a worldwide stock market crash in February and March 2020, created havoc among the investors [10–12]. When economic activities throughout the world were plummeting, surprisingly, in the stock market, the world witnessed the opposite phenomena; the speedy recovery of some stocks and sectors from the crash [10]. These phenomena were also observed during market crashes in 1953–54, 2009 [13]. The study of market crash dynamics and early recovery of the stocks during the crisis is fascinating.

The stocks with strong fundamentals and positive outlook, which are termed as quality stocks, always show strength, universality and persistence in returns [14–16]. The sustainability and resilience of a quality stock depend on its long-term

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growth prospect and financial ability to fulfill shareholder’s demand [17,18]. During crises, the unprecedented economic uncertainty forced the investors towards the quality stocks that may be better able to withstand a downturn, and hence the significant portion of the market capital gets reallocated to these sectors, which in turn pushes the price up [19]. Thus the sectors like pharma, healthcare, food, software and technology showed the quality of withstanding the downturn and recovered quickly from the sharp fall. Whereas sectors like petroleum, real estate, entertainment, hospitality are yet to recover because of grim business outlook [10].

The quality of a company can be quantified by the fundamental determinants such as profit over the assets, return on assets, operating cash-flows to total assets, gross margin, sale growth and some other fundamental determinants that assess the reliabilities of profits, low debt and other measures of sustainable earnings [14–16,20–22]. Investors look for such quality stocks even at a high premium in anticipation of higher returns [14]. The survival and growth of these quality stocks during pandemic depend on the financial antifragility of the company. Financial antifragility is the property that shows the ability of a company to survive from a financial crisis and performs strongly after that, and it mainly depends on the financial liquidity position to mitigate the liabilities [23,24]. The stocks with positive antifragility recover very quickly from uncertain shock and survive and sustain for an extended period [23–25].

The fund flow in the market is primarily determined by the foreign institutional investors (FII) and domestic institutional investors (DII). The purchase/sell activity by the FII and DII also influence the retail investors [26,27]. Hence, the net fund flow due to FII and DII drives the stock price [28–32]. Infusion of a large amount of fund to a particular sector leads to an increase in the stock price or vice versa, i.e., the price movement is strongly correlated with the net fund flow due to FII and DII [31–34]. Generally, during a crisis, the FII and DII look for stocks with robust financial antifragility, and hence these stocks bounce back strongly [19]. Hence modeling and analyzing stock prices in terms of net fund flow and antifragility during shock and recovery phases of a pandemic are essential to understand the market dynamics.

Several models describe the stock price movement using various parameters such as return and dividend [35–37]. The efficient market hypothesis (EMH) states that the future price does not depend on the past behavior of data [38]. Contrary to the EMH hypothesis, some other models show that the stock price is partially predictable [39]. However, the stock price prediction remains a challenging task due to the stock market’s complex nature [40]. Recently, a model of V and L shape recovery of the economy is proposed in Refs. [41,42] depending on the fragility of the individual firms, where the fragility was taken as a ratio between negative cash balance to the wages. So far, no one has modeled and analyzed stock prices in terms of antifragility and fund flow.

The main aim of this paper is to develop a model, and to simulate stock price movement during the COVID-19 shock and subsequent recovery as a function of normalized net fund flow ($\Psi_t$) due to institutional investors and the antifragility parameter of a stock. Model simulation has been carried out for two different sets of $\Psi_t$; (a) $\Psi_t$ obtained from the real fund flow in the market, and (b) artificially generated $\Psi_t$ using the distribution of net cash flow. Simulation with real fund flow reproduces the price movement of the quality stocks and financially stressed stocks during the COVID-19 shock that mimics the actual stock price. The model simulation with artificial data shows the effect of various shock-lengths and antifragility parameters. Further, we have analyzed the stock price using EMD based Hilbert Huang transformation in terms of the time scales of the shock and recovery to identify the quality stocks [43,44].

The rest of the paper is organized as follows: Section 2 describes the formulation of the model. Section 3 discusses the analysis of the simulated results and original stock price. Finally, we have concluded the results in Section 4.

2. Model formulation

A model has been developed for the stock price dynamics of a stock/sector index during the shock and recovery period. The time steps of the model are discrete with a step of one day. The model’s basic assumptions are that the stock price depends on (a) the net fund flow due to FII and DII, and (b) financial antifragility of the company. The basis of the first assumptions is motivated by the finding of the daily stock return is positively correlated with the net fund flow [31,33,34]. The retail investors also flock towards the sector in which FII and DII invest more. Sometimes the price goes up or down with lag to net fund flow because of information delay [31,45]. Hence, the overall market moves with net fund flow due to institutional investors.

During shock, the market falls due to negative sentiment among the investors, leading to a huge outflow of capital from the market. As the pessimism dies down, the investors again come to the market, and invest in those companies which have strong fundamentals and positive growth prospects. Hence, the fund inflow happens to the company with positive antifragility [46,47]. The model with the variables normalized-net-fund-flow and antifragility can capture price dynamics very well during shock and recovery phase.

Let us first define the main ingredients of the model. The variable used in the model is the net fund flow, which can be calculated as follows. The cash purchase (inflow) or sell (outflow) by the FII is denoted as $D_{FI}$ or $D_{FII}$, respectively. Hence, the net cash purchase by the FII is $D_{FI} = D_{FII} - D_{FI}$. Similarly, the cash purchase (inflow) or sell (outflow) by the DII is denoted as $D_{DI}$ or $D_{DII}$, respectively. Hence, the net cash purchase by the DII is $D_{DII} = D_{DII} - D_{DI}$. So (the net fund flow due to DII) the net cash purchase is defined as $D_{DII} = D_{DII} - D_{DII}$. Finally, we obtained $\Delta D_t$ due to the purchase or sale by the institutional investors is $\Delta D_t = D_{FI} + D_{DII}$. Finally, we obtained normalized-net-fund-flow,

$$\Psi_t = \frac{\Delta D_t}{\max(\text{abs}(\Delta D_t))} \tag{1}$$

$\Psi_t$ is the variable that is used to update the stock price.
The second ingredient of the model is the antifragility parameter ($\phi$), which is estimated as follows: The recovery of a company after a shock mainly depends on current asset consumed to fulfill the current liabilities of the company. The asset that is used, sold, consumed or exhausted during a normal operating cycle is called the current assets of a company. The current assets can easily cover day-to-day financial operations and ongoing operating expenses; hence, it becomes a key component for a company’s survival or death. The current assets of the $i$th company, $\chi_i$, is defined as $\chi_i = \eta_{1i} + \eta_{2i} + \eta_{3i} + \eta_{4i}$, where $\eta_{1i}$, $\eta_{2i}$, $\eta_{3i}$, and $\eta_{4i}$ are the current inventories, trade receivables, cash and cash equivalents and other current assets, respectively. Current liabilities are the obligations of a company that consists of short-term debt and other similar debts that will be due within a normal operating cycle. Therefore, we define current liabilities of the $i$th company as $\zeta_i$, where $\zeta_i = y_{1i} + y_{2i} + y_{3i}$, where $y_{1i}$, $y_{2i}$, and $y_{3i}$ are the current debt, trade payable and other current liabilities, respectively. Hence, the liquidity balance of the company is defined as $\chi_i - \zeta_i$. We characterize the financial antifragility ($\phi$) of the $i$th company through liquidity-to-expense ratio

$$\phi_i = \frac{\chi_i - \zeta_i}{\xi_i}$$

(2)

where $\xi_i$ is the operating expenses of a company, and is expressed as $\xi_i = \vartheta_{1i} + \vartheta_{2i} + \vartheta_{3i} + \vartheta_{4i}$, where $\vartheta_{1i}$, $\vartheta_{2i}$, $\vartheta_{3i}$, and $\vartheta_{4i}$ are the employment cost, financial cost, maintenance and operating cost and other financial cost respectively. The $\phi$ for a sector can be written as

$$\phi = \frac{\sum_{i=1}^{N} \phi_i}{N}$$

(3)

where $N$ is number of company in any sector’s index. $\phi$ acts as the control parameter of the price movement. The value of $\phi > 0$ for a quality stock, and $\phi < 0$ for a financially stressed stock. Usually, $\phi$ get updated twice a year based on the financial statement of a company. It is important to mention that during shock, market nose dives due to massive sell-off by the investors, and hence the price movement is independent of $\phi$.

Our model updates the stock price as a function of $\Psi_t$ using the parameter $\phi$ as follows

$$P_{t+1} = P_t[1 + \lambda \Psi_t], \quad \text{During shock}$$

(4)

$$P_{t+1} = P_t[1 + \lambda \Psi_t \phi], \quad \text{Otherwise}$$

(5)

where, $\lambda$ is the coefficient of $\Psi_t$ that represents the proportion of the net fund by the institutional investors that flows in a particular company/sector. The value of $\lambda$ changes during normal, shock and recovery period. The value of $\lambda$ has been taken on ad hoc basis depending on the normalized fund flow due to the mutual fund and FPI. Typically the value of $\lambda$ is in the range of $0 \leq \lambda \leq 1$.

There are large numbers of companies and indices in the stock market. To understand the price movement of these companies and indices during the COVID-19 shock, one needs to study the model with different shock and recovery lengths and antifragility parameters. Hence, in Section 2.1, the model equations [Eqs. (4) and (5)] is simulated using artificially generated fund flow data to understand the COVID-like shock. The artificial data is generated from the normal distribution of real fund flow during different phases of the COVID crisis. Further, the model is studied in Section 2.2 for the COVID-19 shock by using real fund flow and antifragility of the company.

2.1. COVID-like shock

Study of the effect of the COVID-like shock on the stock prices in terms of various shock lengths ($T_{S}$) and different $\phi$ is very important to understand the market crash and subsequent recovery. We have generated synthetic normalized fund flow ($\Psi_{st}$) data from the distribution of $\Psi_t$ [Eq. (1)] during the normal, shock and recovery period. The distribution of $\Psi_t$ for the normal, shock and recovery periods are $\mathcal{N}(0, 0.17)$, $\mathcal{N}(-0.2, 0.49)$ and $\mathcal{N}(0.06, 0.22)$, respectively, and accordingly $\Psi_{st}$ is generated. As the distribution of the $\Psi_t$ is derived from real data, the $\Psi_{st}$ mimics the real situation. In this model simulation, the recovery time period ($T_{R}$) is taken equal to $T_{S}$, and the justification is given in detail in Section 3.3. The value of $\lambda = 0.2$, 0.1, 0.7, 0.3 during pre-covid normal period, shock period, recovery period and post recovery period, respectively. The reason for choosing different values of $\lambda$ during different periods is discussed in Section 2.2.

To understand the V-shape recovery of a quality stock, the model simulation is carried out for the fixed $\phi = 0.4$ with $T_{S} = 20$ day (D), 40 D, 60 D, and 80 D, respectively, and for the fixed $T_{S} = 20$ D with $\phi = 0.3$, 0.4, 0.5 and 0.6. The value of $\phi$ and $T_{S}$ are chosen based on the original stock price. Similarly, for the L-shape recovery of the financially stressed company, simulation is carried for the $\phi = -0.08$ with $T_{S} = 20$ D, 40 D, 60 D, and 80 D, respectively, and for the $T_{S} = 20$ D with $\phi = -0.05$, $-0.15$, $-0.25$ and $-0.35$. In this case, the value of $\phi$ and $T_{S}$ are chosen on the basis of the original stock price. The detailed simulation result is given in Section 3.

2.2. COVID-19 shock

The model simulation has been carried out for the stock price during the COVID-19 using the $\Psi_t$ and $\phi$ for the Indian market. The $\Psi_t$ has been calculated from real net fund flow in the market due to FI and DI using Eq. (1). The fund flow data has been obtained from the money control website [48]. The current financial status of a company, $\phi$, is estimated using
Fig. 1. Plot (a) shows the monthly data of the normalized fund flow due to mutual fund in Pharma (− PH), FMCG (− FMCG) and Hotel and Tourism (− HRT) sectors. Plot (b) shows the fortnightly data of the normalized fund flow due to FPI in Pharma (− PH), FMCG (− FMCG) and Hotel and Tourism (− HRT) sectors.

Eq. (2). The value of $\phi$ for a sector has been calculated using Eq. (3). The current assets, current liabilities and expenses of a company have been derived from its financial statements, which are obtained from Bombay Stock Exchange Ltd (BSE) [49].

The coefficient $\lambda$ for a particular stock depends on the ratio of fund flow to total fund flow in the market. In the present case, the value of $\lambda$ is taken in ad hoc manner that can be guessed from the fund flow to a sector due to the institutional investors. Fig. 1(a) shows the normalized monthly fund flow due to mutual fund investors (MFI) in Pharma & Biotechnology (− PH), Fast Moving Consumers good (− FMCG) and Hotel Restaurant and tourism (− HRT). The above sector data has been obtained from the Securities and Exchange Board of India (SEBI) [50]. Fig. 1(b) shows the normalized fortnightly fund flow due to foreign portfolio investors (FPI) in Pharma & Biotechnology (− PH), Fast Moving Consumers good (− FMCG) and Hotel Restaurant and tourism (− HRT), and the data has been obtained from National Securities Depository Ltd., India (NSDL) [51]. The figure shows that the fund flow during shock decreased significantly, and during the recovery phase, fund flow in the Pharma and FMCG sectors increased significantly. On the other hand, in the Hotel Restaurant and tourism sector, fund flow remains almost constant after a drastic drop. Considering the above information, for the quality stock, we have taken $\lambda = 0.6, 0.2, 0.8, 0.6$ for Nifty Pharma and $\lambda = 0.6, 0.4, 0.9, 0.7$ for Nifty FMCG index during the pre-COVID normal period, shock period, recovery period and post-recovery period, respectively, and for a financially stressed stock, like Tata Motors Ltd., $\lambda = 0.6, 1.0, 0.8, 0.7$ and for BPCL $\lambda = 0.6, 0.8, 0.8, 0.7$ during the above four periods. The detailed simulation result is given in Section 3.

3. Results and discussion

This section aims to present the simulation results of the effect of the $T_S$ and $\phi$ on the V- and L-shape recovery of the stock price. The analysis of the original price and the simulated price has also been carried out to identify the shock and recovery time scales of the stock price.
Plot (a) shows the V-shape recovery using the synthetic data for fixed $\phi = 0.4$ with $T_S = 20\text{ D}$, $40\text{ D}$, $60\text{ D}$ and $80\text{ D}$. Plot (b) shows the V-shape recovery using synthetic data for fixed $T_S = 20\text{ D}$ with $\phi = 0.3$, $0.4$, $0.5$ and $0.6$. $D$ and $\phi$ represent day and financial antifragility. Vertical dashed line represents the starting point of shock. For the simulation initial condition is taken as 0.5.

3.1. Simulation of COVID-like shock

Fig. 2(a) shows the typical plot of V-shape recovery of a quality stock using $\Psi_n$ for different $T_S$ with $\phi = 0.4$. As the typical value of $\phi$ for a quality sector is around 0.4. The plot $\cdots$, $\cdots$, $\cdots$, and $\cdots$ show the stock price movement for the $T_S = 20\text{ D}$, $40\text{ D}$, $60\text{ D}$, and $80\text{ D}$, respectively. The results show that the quality stock recovers very well to its pre-shock price for the $T_S = 20\text{ D}$ and $40\text{ D}$. However, when the shock extended beyond $60\text{ D}$, it becomes difficult to recover because of the stock price’s serious crash. It implies that the extended period of $T_S$ is harmful even for the financially strong company. During such kind of extended shock, the investor stays away from investment in the market, which is sometimes termed by the investors “Do not catch a falling knife” [52].

Fig. 2(b) shows the typical plot of V-shape recovery of quality stocks for different $\phi$ with $T_S = 20\text{ D}$. The typical value of $T_S$ was 20 D during the COVID-19 for a quality sector. The plot $\cdots$, $\cdots$, $\cdots$, and $\cdots$ show the stock price movement for the $\phi = 0.3$, $0.4$, $0.5$ and $0.6$, respectively. The higher the value of $\phi$, the recovery is rapid. The results show that the quality stock recovers very well for positive $\phi$. Further, the quality stocks with higher $\phi$ outperform its peer. Hence, the financially strong company recover from the shock and outperform compared to another company observed during the COVID-19 [46,47]. During crises, the investors invest heavily in such companies, and hence generates higher return [53].

Fig. 3(a) shows the typical plot of L-shape recovery of a financially stressed stock for different $T_S$ with $\phi = -0.08$. The plot $\cdots$, $\cdots$, $\cdots$, and $\cdots$ show the stock price movement for the $T_S = 20\text{ D}$, $40\text{ D}$, $60\text{ D}$, and $80\text{ D}$ respectively. The simulation results show that the financially stressed stock does not recover. As the value of $T_S$ increases, the negative depth of stock price also increases. So, a financially stressed company cannot survive the extended $T_S$, and have a big chance to die down. The investors become very bearish on these company, and sell-off their positions, and hence the chance of the recovery of the stock price also becomes marginal.

Fig. 3(b) also shows the typical plot of the L-shape behavior of a financially fragile stock for different $\phi$ with $T_S = 20\text{ D}$. The plot $\cdots$, $\cdots$, $\cdots$, and $\cdots$ show the stock price movement for the $\phi = -0.05$, $-0.15$, $-0.25$ and $-0.35$, respectively. For the simulation of COVID-like shock we have taken 0.5 as initial condition. The company with negative $\phi$ continues to slide down even during the recovery phase of the overall market. The lower the $\phi$, the slide in stock price is rapid. So, a company with a lower $\phi$ has a big chance to die down. As the investors stay away from these companies, the chance of the stock price recovery also becomes marginal as mentioned in the previous paragraph.
3.2. COVID-19 shock

Figs. 4(a) and 4(b) show the simulation result (— ) of the model using the $\Psi_t$ given in Eq. (1), and — represents stock price of the Pharma and FMCG index in Indian market during the COVID-19 shock. The simulation results of Pharma and FMCG indices show that the fall of the stock price due to the COVID-19 shock starts from 1st week of March 2020, and forms a bottom on 4th week of April 2020, as shown in Fig. 4(a) and Fig. 4(b), respectively. The model simulation shows a V-shape recovery in the stock price consistent with the original stock price during the shock, as shown in the same figure. We observed a lag in the formation of the bottom between the model simulation data (SD) and original data (OD). Original stock price recovers earlier than the model. The possible reason for such lag may be due to the fund allocation in the quality sectors by the investors internally, which was not reflected in the fund flow. For example, in India, during the pandemic, the outlook in the Pharma and FMCG sectors becomes positive, hence the fund allocation to these sectors due to DII and retail investors increased rapidly that can be understood only from investors’ buying sentiment. The model for the quality index and company may behave properly with minimum lag if index or company wise fund flow data were available.

Figs. 5(a) and 5(b) show the simulation result for the stock price that show L-shape recovery in Indian market during COVID-19 shock. The simulation for Tata Motors Ltd., and BPCL show that the fall of the stock price due to the COVID-19 shock starts from 1st week of March 2020, and forms a bottom on 4th week of March 2020 as shown in Fig. 5(a) and Fig. 5(b), respectively. We observed that the stock with $\phi < 0$ does not recover from the bottom, i.e., the behavior of the price is L-shape, as shown in the same figure. The main reasons for the poor allocation of the fund in these stressed stocks are the non-essential nature of the product they produce, negative outlook during COVID-19.

3.3. Time scale analysis

The empirical mode decomposition (EMD) technique is applied to identify the important $T_S$ and $T_R$ of stocks and indices during the COVID-19 [54,55]. The EMD technique decomposes a signal into a number of intrinsic mode functions (IMF) of different time scales by preserving the nonlinearity and nonstationarity of a time series [56]. The detailed algorithms for identifying the IMF using the EMD method is given in Refs. [44,54].
Fig. 4. Plot (a) represents the original stock price movement of Nifty Pharma (−OD) and its corresponding model simulated stock price movement (− − SD) with \( \phi = 0.41 \) and \( \tau_S = 20 \) D. Plot (b) represents the original stock price movement of Nifty FMCG (−OD) and its corresponding model simulated stock price movement (− − SD) with \( \phi = 0.21 \) and \( \tau_S = 20 \) D.

Fig. 5. Plot (a) shows the original stock price movement of Tata Motors Ltd., (−OD) and its corresponding model simulated stock price movement (− − SD) with \( \phi = -0.077 \) and \( \tau_S = 20 \) D. Similarly, plot (b) shows the original stock price movement of BPCL (−OD) and its corresponding model simulated stock price movement (− − SD) with \( \phi = -0.052 \) and \( \tau_S = 20 \) D.

The range of a time period of a particular IMF can be obtained using \( \tau = \frac{1}{\omega} \), where \( \omega = \frac{d\theta(t)}{dt} \). The \( \omega \) of a particular IMF can be estimated by using Hilbert Transform, which is defined as

\[
Y(t) = \frac{p}{\pi} \int_{-\infty}^{\infty} \text{IMF}(t) \frac{dt}{t-t'}
\]
where $P$ is the Cauchy principle value, and $\theta(t) = \tan^{-1}\left(\frac{Y(t)}{IMF(t)}\right)$ [54]. We have applied EMD based Hilbert Huang Transformation to obtain the $\tau$ of the stock data.

We have identified the $\tau$ of the Nifty Pharma and Nifty FMCG index as quality stocks, and their model simulated data during the COVID-19 shock. The data were taken from [57,58].

Fig. 6 shows the IMF of the Nifty Pharma index estimated using the EMD technique. The series is decomposed into four IMFs and a residue. Fig. 6 shows the visualization. IMF1 represents the signal with the lowest $\tau$, and the $\tau$ increases with the increase in IMF numbers. The residue represents the overall long-term trend of the index. Each IMF represents a mono-frequency component of the stock data.

In order to identify the $\tau$ of the COVID-19 shock and subsequent recovery of the quality stocks, we have first identified the dominant IMF that fits the event as follows. We have calculated the correlation coefficient (\(\nu\)) between the original stock price and its IMFs and model-simulated stock price and its IMFs. We have also calculated variance (\(\sigma^2\)) of the IMFs as shown in Table 1. The value of $\nu$ measures the relationship between the individual IMF and the stock price. Whereas, the value of $\sigma^2$ measures the volatility of each IMF. From Table 1, the values of $\nu$ and $\sigma^2$ shows that the IMF4 is the dominant mode for the original pharma and FMCG index and their model simulated data. All the four IMF4 modes along with their time series are shown in Figs. 7(a)–7(d), respectively. The average $\tau$ of the IMF4 for the pharma, FMCG index and simulated pharma and FMCG are approximately 57 $\tau$, 56 $\tau$, 58 $\tau$ and 58 $\tau$, respectively. Vertical lines in the figure show the bottom formation due to the COVID-19 shock. All the IMF4 shows that $\tau_S$ and $\tau_R$ are almost equal. For the pharma and FMCG stocks $\tau_S \approx \tau_R \approx 28 \tau$. We have obtained that the $\tau_S \approx \tau_R$ for all the quality stocks that show V-shape recovery. It is pertinent to mention that there is no dominant mode present in the case of L-shape recovery.

![Image](image-url)
4. Conclusion

In this paper, we have developed a model of the stock price movement during the COVID-19 shock and its subsequent recovery. The simulation is carried out assuming that during shock, the price crashes due to the fund outflow from the market, and does not depend on the financial antifragility ($\phi$) of a company. Whereas, the recovery of the stock price depends on the fund inflow towards a particular company or sector depending on $\phi$. The model simulates the stock price for different $T_S$ and different $\phi$ using synthetic normalized net fund flow. The model reproduces the stock price movement during the pandemic very well. We have also identified the $T_S$ and $T_R$ from the model and original data using EMD based Hilbert Huang Transformation.

We obtained V-shape recovery of the quality stocks with positive $\phi$ using synthetic normalized net fund flow ($\Psi_{st}$). The stock price recovers very well to its pre-shock value for the $T_S = 20 D$ and $40 D$ with fixed $\phi = 0.4$. However, when the $T_S$ extends beyond 60 D, it becomes difficult for the stock price to recover to its pre-shock price. We also obtained the V-shape recovery for $\phi = 0.3, 0.4, 0.5$ and 0.6 with fixed $T_S = 20 D$. The stock with a higher $\phi$ outperforms its peer with a lower $\phi$ after crises. Such performance in the stock price of certain quality stocks have been observed during the COVID-19 pandemic. In the case of the financially stressed stocks, i.e., with negative $\phi$, we obtained L-shape recovery of the stock price, and such stocks show higher negative depth in stock price with an increase in $T_S$. As the value of $\phi$ decreases, the duration of $T_S$ increases that have been observed in several stocks during the pandemic.

We obtained V-shape recovery from the model using the normalized net fund flow $\Psi_t$. In this simulation, we have used the average value of $\phi$ of the Pharma and FMCG. The simulated results are consistent with the original stock price movement of the Pharma and FMCG indices during the COVID-19 shock. On the other hand, for the companies with negative $\phi$, the model also consistent with L-shape movement of price.

Finally, we obtained that the $T_S$ and $T_R$ of a quality stock during the COVID-19 is approximately equal. On the other hand, the companies with $\phi < 0$ is yet to recover. The value of $T_S$ and $T_R$ for different sectors will be useful for making an investment decision. We observed that for some sectors like the banking where $\phi > 0$, it still shows L-shape recovery. Such recovery depends on various other factors which will be studied in future work.

CRediT authorship contribution statement

Ajit Mahata: Conceptualization, Writing - original draft, Software, Validation, Formal analysis, Resources. Anish Rai: Formal analysis, Investigation, Resources. Md. Nurujjaman: Supervision, Conceptualization, Writing - original draft, Software, Validation, Formal analysis, Resources. Om Prakash: Conceptualization, Writing - original draft, Software, Validation, Formal analysis.
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.

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References

[1] S. Muhammad, X. Long, M. Salman, COVID-19 pandemic and environmental pollution: a blessing in disguise? Sci. Total Environ. (2020) 138820.
[2] R.J. Barro, J.F. Ursúa, J. Weng, The Coronavirus and the Great Influenza Pandemic: Lessons from the “Spanish Flu” for the Coronavirus’s Potential Effects on Mortality and Economic Activity, Technical Report, National Bureau of Economic Research, 2020.
[3] B.N. Ashraf, Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets, J. Behav. Exp. Finance 27 (2020) 100371.
[4] M. Topcu, O.S. Gulal, The impact of COVID-19 on emerging stock markets, Finance Res. Lett. (2020) 101691.
[5] F.R. Velde, What happened to the us economy during the 1918 influenza pandemic? a view through high-frequency data, FRB of Chicago Working Paper No. WP-2020-11, 2020.
[6] Ö. Jordà, S.R. Singh, A.M. Taylor, Longer-Run Economic Consequences of Pandemics, Technical Report, National Bureau of Economic Research, 2020.
[7] S.R. Baker, N. Bloom, S.J. Davis, K. Kost, M. Sammon, T. Virayatsoin, The unprecedented stock market reaction to COVID-19, Rev. Asset Pricing Stud. (2020).
[8] J.W. Goodell, COVID-19 and finance: Agendas for future research, Finance Res. Lett. (2020) 101512.
[9] P.K. Narayan, D.H.B. Phan, G. Liu, COVID-19 lockdowns, stimulus packages, travel bans, and stock returns, Finance Res. Lett. (2020) 101732.
[10] M. Mazur, M. Dang, M. Vega, COVID-19 and the march 2020 stock market crash. Evidence from S&P1500, Finance Res. Lett. (2020) 101690.
[11] D. Zhang, M. Hu, Q. Ji, Financial markets under the global pandemic of COVID-19, Finance Res. Lett. (2020) 101528.
[12] https://www.bbc.com/news/business-51796806.
[13] https://www.forbes.com/sites/billconerly/2020/08/03/what-is-the-stock-market-trying-to-tell-us-about-the-economy-and-should-we-listen/#c97d5f1683.
[14] C.S. Asness, A. Frazzini, L.H. Pedersen, Quality minus junk, Rev. Account. Stud. 24 (1) (2019) 34–112.
[15] J.-P. Bouchaud, S. Ciliberti, A. Landier, G. Simon, D. Thesmar, The excess returns of "quality" stocks: a behavioral anomaly, 2016, arXiv preprint arXiv:1601.04478.
[16] R. Novy-Marx, The other side of value: The gross profitability premium, J. Financ. Econ. 108 (1) (2013) 1–28.
[17] N.R. Castro, J.P. Chousa, An integrated framework for the financial analysis of sustainability, Bus. Strategy Environ. 15 (5) (2006) 322–333.
[18] D.D. Lee, R.W. Faff, Corporate sustainability performance and idiosyncratic risk: A global perspective, Financial Rev. 44 (2) (2009) 213–237.
[19] https://www.wsj.com/articles/investors-rush-into-quality-stocks-11570413961.
[20] G. Charest, Dividend information, stock returns and market efficiency—II, J. Financ. Econ. 6 (2–3) (1978) 297–330.
[21] S. Basu, Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis, J. Finance 32 (3) (1977) 663–682.
[22] J.C. Bhandari, Debt/equity ratio and expected common stock returns: Empirical evidence, J. Finance 43 (2) (1988) 507–528.
[23] N.N. Taleb, R. Douday, Mathematical definition, mapping, and detection of (anti) fragility, Quant. Finance 13 (11) (2013) 1677–1689.
[24] N.N. Taleb, Antifragile: Things That Gain from Disorder, vol. 3, Random House Incorporated, 2012.
[25] J.J. Platje, et al., Sustainability and antifragility, Econ. Environ. Stud. 15 (4 (36)) (2015) 469–477.
[26] C. Cao, E.C. Chang, Y. Wang, An empirical analysis of the dynamic relationship between mutual fund flow and market return volatility, J. Bank. Financ. 32 (10) (2008) 2111–2123.
[27] B.M. Barber, T. Odean, N. Zhu, Do retail trades move markets? Rev. Financ. Stud. 22 (1) (2008) 151–186.
[28] J. Coval, E. Stafford, Asset fire sales (and purchases) in equity markets, J. Econom. 86 (2) (2007) 479–512.
[29] N. Ülkü, E. Weber, Identifying the interaction between foreign investor flows and emerging stock market returns, Rev. Finance 18 (4) (2014) 1541–1581.
[30] G. Kling, L. Gao, Chinese institutional investors’ sentiment, J. Int. Financial Mark. Inst. Money 18 (4) (2008) 374–387.
[31] R.M. Edelean, J.B. Warner, Aggregate price effects of institutional trading: a study of mutual fund flow and market returns, J. Financ. Econ. 59 (2) (2001) 195–220.
[32] P. KP, Dynamics of foreign portfolio investment and stock market returns during the COVID-19 pandemic: Evidence from India, Asian Econ. Lett. 1 (2) (2020) http://dx.doi.org/10.46655/001c.17658.
[33] R.M. Edelean, Investor flows and the assessed performance of open-end mutual funds, J. Financ. Econ. 53 (3) (1999) 439–466.
[34] V.A. Warther, Aggregate mutual fund flows and security returns, J. Financial Econ. 39 (2–3) (1995) 209–235.
[35] Z. Ding, C.W. Granger, R.F. Engle, A long memory property of stock market returns and a new model, J. Empir. Finance 1 (1) (1993) 83–106.
[36] T.A. Marsh, R.C. Merton, Dividend behavior for the aggregate stock market, J. Bus. (1987) 1–40.
[37] T.A. Marsh, R.C. Merton, Dividend variability and variance bounds tests for the rationality of stock market prices, Am. Econ. Rev. 76 (3) (1986) 483–498.
[38] E.F. Fama, Efficient capital markets: A review of theory and empirical work, J. Finance 25 (2) (1970) 383–417.
[39] B.G. Malkiel, The efficient market hypothesis and its critics, J. Econ. Perspect. 17 (1) (2003) 59–82.
[40] M. Ballings, D. Van den Poel, N. Hespeels, R. Gryp, Evaluating multiple classifiers for stock price direction prediction, Expert Syst. Appl. 42 (20) (2015) 7046–7056.
[41] D. Sharma, J.-P. Bouchaud, S. Gualdi, M. Tarzìa, F. Zamponi, V., L-or W-shaped recovery after covid? Insights from an agent based model, insights from an agent based model (June 15, 2020), 2020.
[42] S. Gualdi, M. Tarzìa, F. Zamponi, J.-P. Bouchaud, Tipping points in macroeconomic agent-based models, J. Econom. Dynam. Control 50 (2015) 29–61.
[43] L. Menkhoff, The use of technical analysis by fund managers: International evidence, J. Bank. Financ. 34 (11) (2010) 2573–2586.
[44] A. Mahata, D.P. Bal, M. Nurujjaman, Identification of short-term and long-term time scales in stock markets and effect of structural break, Physica A 545 (2020) 123612.

[45] L. Sun, M. Najand, J. Shen, Stock return predictability and investor sentiment: A high-frequency perspective, J. Bank. Financ. 73 (2016) 147–164.

[46] S. Glossner, P. Matos, S. Ramelli, A.F. Wagner, Where do institutional investors seek shelter when disaster strikes? Evidence from COVID-19, CEPR Discussion Paper No. DP15070, 2020.

[47] R. Fahlenbrach, K. Rageth, R.M. Stulz, How Valuable Is Financial Flexibility When Revenue Stops? Evidence from the Covid-19 Crisis, Technical Report, National Bureau of Economic Research, 2020.

[48] https://www.moneycontrol.com/.

[49] https://www.bseindia.com/.

[50] https://www.sebi.gov.in/.

[51] https://nsdl.co.in/.

[52] J.-E. Colliard, Catching falling knives: Speculating on market overreaction, ECB Working Paper, 2013.

[53] https://www.bloombergquint.com/markets/stocks-in-the-post-covid-world-what-now-for-investors.

[54] N.E. Huang, Z. Shen, S.R. Long, M.C. Wu, H.H. Shih, Q. Zheng, N.-C. Yen, C.C. Tung, H.H. Liu, The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis, Proc. R. Soc. A 454 (1971) (1998) 903–995.

[55] N.E. Huang, Hilbert-Huang Transform and Its Applications, vol. 16, World Scientific, 2014.

[56] N.E. Huang, M.-L. Wu, W. Qu, S.R. Long, S.S. Shen, Applications of Hilbert–Huang transform to non-stationary financial time series analysis, Appl. Stoch. Models Bus. Ind. 19 (3) (2003) 245–268.

[57] https://in.finance.yahoo.com/.

[58] https://www.nseindia.com/.