Investors’ Emotions and Mean-Reversion in Stock Prices

David Bourghelle (IAE Lille University School of Management, France)
Pascal Grandin (IAE Lille University School of Management, France)
Fredj Jawadi (IAE Lille University School of Management, France)
Philippe Rozin (IAE Lille University School of Management, France)

Abstract

The US stock market has displayed considerable excess volatility during the different waves of the COVID-19 pandemic. Notably, while most US indexes fell abruptly and lost about 20%-30% during the first wave and in times of lockdown, unlike the global financial crisis of 2008-2009, the correction was rapid, and most stock indexes subsequently exceeded their pre-COVID levels. Accordingly, it is important to assess whether this dynamic is driven more by a switch in fundamentals or whether it is simply due to a conversion of investors’ emotions. This chapter aims to analyze the dynamics of the US (S&P500) stock index both before and during the ongoing coronavirus pandemic. Our findings point to three interesting results. First, US stock returns are driven by both macro-financial and behavioral factors. Second, a two-regime multifactorial model reproduces the dynamics of the US market in which financial factors play a key role whatever the regime, while the impact of behavioral factors appears more significant only in the second regime when investors’ anxiety exceeds a given threshold. Third, our in-sample forecasts point to the superiority of our nonlinear multifactorial model to forecast the dynamics of the US stock market.

Keywords: COVID-19, stock indexes, fundamentals, investors’ emotions, nonlinear multifactorial model
JEL: C2, F10, G10.

1. Introduction

"*Are Markets Efficient?*" is the title of a fascinating interview between Eugène Fama and Richard Thaler organized on 30 June 2016. This interview, which is available at https://www.youtube.com/watch?v=bM9bYOBuKF4, has received 195,087 views to date. While the two professors of Economics from the University of Chicago are also recipients of the Nobel Prize in Economics (in 2013 and 2017 respectively), they expound different views about price formation and how markets behave and misbehave. Interestingly, while Eugène Fama defends the hypothesis of rationality, the informational efficiency theory by which prices reflect the overall information set instantaneously and fully, asserting that fundamentals play a key role in driving the prices of financial assets, Richard Thaler instead explains that human miscalculations, psychology, and therefore behavioral economics, play a key role in helping us to better understand the dynamics of financial markets.

The question remains open, especially when considering the excessive volatility of capital market in times of COVID-19. Indeed, the ongoing coronavirus pandemic has had a significant impact on the main equity markets, resulting in considerable volatility. While stock markets corrected and lost about 30% in March 2020, unlike the global financial crisis of 2008-2009, their recovery was rapid and abrupt from May 2020 onwards. According to Bourghelle *et al.* (2022), two factors can explain this excess volatility during the COVID-19 outbreak. On the one hand, the pandemic caused a supply and demand shock on economic activity for different sectors and firms. Accordingly, several banks and firms cut or revised their dividend policies, thereby impacting the prices of financial assets and trade. On the other hand, the COVID-19 shock led to greater uncertainty and fear of investment, impacting on investors' risk premium. In other words, both dividends and risk premiums evolved during the COVID-19 pandemic and, interestingly, their evolution varied with the progress of the pandemic and the anti-COVID policies (lockdown, central bank's policies, teleworking, etc.). Consequently, capital markets have undergone diverse episodes since 2020.

From this perspective, it appears that the financial markets might still be driven by fundamentals and thus be sensitive to the actions of central banks. However, it is also clear that investors remain sensitive to the level of uncertainty regarding the whole economy and the underlying economic policies. The focus on this economic and political uncertainty as well its evolution in a high inflation environment may generate specific emotions and perceptions of risk. This is confirmed when we look at the impressive evolution of the VIX index in 2020. Indeed, during the first wave of COVID-19, the VIX index rose by over 45%.

This chapter examines the dynamics of the US stock market over the two last decades, especially in the context of COVID-19. To this end, we explain the dynamics of the US stock market (S&P500) over the period 2000-2021 using three sets of factors. The first set encompasses key macroeconomic variables (unemployment rate, inflation rate, interest rate). The second set of factors includes financial variables (dividends, earnings, bond returns). The third set includes a series of behavioral factors (investors' sentiment, uncertainty, VIX), as well as some proxies to capture COVID-19 news. The main motivation of this study is to check whether further shift in investor behavior and/or subsequent structural changes in financial and economic factors induced by the pandemic have been driven the US stock market. In this way, we wish to measure the impact of COVID-19 on investment patterns in a situation of high uncertainty.

Econometrically, we applied a sequential econometric model that enabled us to build different specifications to assess the dynamics of the US stock market. In particular, we estimated the contribution of these different factors to explain the evolution of the US stock market. We allowed our model to be as flexible as possible to capture the US stock market dynamics in its different market states and episodes.

Our results show first that US stock returns are driven by both macro-financial and behavioral factors. Second, a two-regime multifactorial model effectively reproduces the dynamics of the US market in which financial factors play a key role whatever the regime, whilst the action of behavioral factors appears more significant only in the second regime when investors' anxiety exceeds a given threshold. Third, our in-sample forecasts point to the superiority of our nonlinear multifactorial model to forecast the dynamics of the US stock market. In fact, our findings in this chapter are consistent with an on-going literature in behavioral finance including Bandopadhyaya and Truong (2010) for which the hypothesis of active interaction between market participants, market sentiment and asset prices is not rejected. Interestingly, our results contribute while pointing to nonlinearity and regime switching in sentiment –asset price relationship.

The chapter is organized as follows. Section 2 briefly presents the related literature. The econometric modeling steps and the main empirical results are discussed in section 3. Section 4 concludes.

2. Literature

The COVID-19 crisis can be viewed as an exogenous shock, but it has reset our understanding of crises and cycles of major economic downturns and their causes (Goldstein, Koijen, Mueller, 2021). Thus, several studies agree that the ongoing COVID-19 pandemic has had a significant but also a complex and time-varying impact on the main financial markets and economies. The effect of the COVID-19 shock has been significant, with many capital markets reporting significant corrections during the different waves of the pandemic. Further, the COVID-19 effect is both complex and time-varying as, while most financial markets corrected during the first COVID-19 wave, they subsequently recovered very rapidly, evolving in line with the progress of the pandemic. Interestingly, the latter has transformed the perception of risk in the market and has had a substantial impact on beliefs and behavior. For instance, the expectation of public stimulus measures following the shut-down of trade in many European countries and the ensuing government intervention has profoundly transformed investors' reactions and behavior.

In addition, management of the pandemic by most of the world's governments also had an impact on financial assets and their prices. Indeed, fiscal and monetary authorities responded to the pandemic with unprecedented force. Governments around the world engaged in large-scale stimulus measures to prevent mass layoffs and bankruptcies. Similarly, while monetary policy was exceptionally accommodative to avoid a sudden tightening of credit conditions and liquidity shortages, the effects of the crisis were mitigated by the use of a variety of policies. While these policies undoubtedly mitigated the negative economic effects of the pandemic, they have had an undeniable inflationary impact over time. Accordingly, this inflationary pressure may not only impact investment and financial markets, but also increase uncertainty, fear, and investors' anxiety.

Several authors in the recent literature have analyzed the effects of these factors and the COVID-19 environment on the financial markets. For example, Aspergis and Aspergis (2021) showed that COVID-19 had a positive impact on inflationary volatility. Based on the standard deviation of COVID-19-related deaths both in the US and globally, they concluded that mortality significantly increases average inflation. The transmission of the COVID-19 virus, as measured by the number of cases and deaths, caused an unprecedented shock to the stock markets. There are also many questions regarding how the markets will react. Government measures and highly accommodative monetary policy may support the equity market up to a point, but for how long?

Cappelle-Blancard & Desroziers (2020) assessed how the stock markets integrated public information about COVID-19, the subsequent lockdowns, and the policy reactions, concluding that while the COVID-19 shock was global, not all countries were impacted in the same way. They showed that prior to February 21, stock markets initially ignored the pandemic, then reacted strongly to the growing number of infected people (between Feb. 23

to Mar. 20), while volatility surged as concerns about the pandemic rose. Nevertheless, following the intervention of central banks (Mar. 23 to Apr. 30), shareholders no longer seemed troubled by news of the health crisis, and prices rebounded across the globe.

Landier & Thesmar (2020) analyzed the dynamics of earnings forecasts and discount rates implicit in valuations during the COVID-19 crisis. Using stock prices of firms traded on NYSE, Nasdaq, and Amex at the end of 2019, and I/B/E/S forecasts through the Refinitiv-Eikon platform (Thomson Reuters), they estimated an implicit discount rate that rose from 8.5% in mid-February to 11% at the end of March, before reverting to its initial level in mid-May. Over this period, the unlevered asset risk premium increased by 50bp, while the risk-free rate decreased by 100bp. They showed that analysts' forecast revisions explained all the decreases in equity values between January 2020 and mid-May 2020.

Sergi, Harjoto, Rossi and Lee (2021) found that the contraction of real GDP growth and the rise in unemployment, inflation, and long-term interest rates had a negative impact on stock returns and increased stock market volatility. They also demonstrated a particularly important point: the increase in COVID-19-related cases and deaths exacerbated the negative impact of changes in the equity market misery index.

Vasileiou (2021) used two models to examine US stock market performance during the COVID-19 epidemic, a fundamental financial analysis approach and a behavioral model including a Google-based index. They showed that during certain periods, the health risk was significantly underestimated and often completely ignored. Their most important finding was that one systemic factor, namely, health risk, is far from being rationally incorporated into stock prices. Using a coronavirus fear index (CFI) based on Google searches and Granger causality, they showed that fear drives the performance of the S&P500, negatively influencing the US stock market performance.

In the same context, and using a behavioral finance framework, Bansal (2020) examined phenomena that were particularly intense during the crisis (excessive volatility and unshakable confidence in financial institutions), examining them specifically during the COVID-19 crisis.

In turn, Subramaniam and Chakraborty (2021) investigated the impact of fear of COVID-19 on stock market returns. Using a COVID-19 fear index construction based on Google Trends, they measured the mood of individual investors during the pandemic. Their results suggest a negative impact of COVID-19 fear on stock returns, which appears to cumulatively persist even up to five days. This relationship has a persistent effect on stock prices over a significant period of time.

Ortmann, Pelster and Wengerek (2020) investigated how retail investors responded to the COVID-19 outbreak. Using trade-level data, they showed that investors increased their brokerage deposits and opened more new accounts, noting that average weekly trading intensity increased significantly when the number of COVID-19 cases doubled. In particular, investors opened more positions in equities and indices but did not move into safe haven investments (gold) or particularly "risky" investments (equity CFDs, cryptocurrencies).

Baker et al. (2020) used text-based methods to study the reaction of markets to different pandemics (including COVID-19) since 1900. They showed that the unprecedented reaction to COVID-19 is related to health and social distancing measures and the anticipated effects on the economy. Gormsen and Koijen (2020) wrote an interesting paper in which they showed how the COVID-19 has changed investors' dividend expectations (comparative analysis of the EU and the US). Albulescu (2021) showed that it is the announcements made by the monetary authorities that have impacted the volatility of US stock prices. A paper by Igan et al. (2020) showed that central bank intervention has disconnected financial markets from the real economy, and that this has lifted asset valuations. Mazur et al. (2021) linked the COVID-19 crisis to the S&P stock market crash of March 2020. Some articles are very directly related to our research question, in particular the links between asset price volatility and emotions, captured by uncertainty and emotions. Chundakkadan and Nedumparambi (2021) proposed a comprehensive study on 59 countries showing the nexus between investors' attention to COVID-19 and daily asset returns. Lee (2020) used big data to study the impact of COVID-19 sentiment on the US equity market. Yu et al. (2022) analyzed the co-movement between COVID-19 pandemic anxieties and stock market returns.

These recent studies are in line with the literature on behavioral finance, which offers an interesting framework for studying the way in which investors' choice criteria and judgments are formed in financial markets. This idea was initiated by De Bond and Thaler (1995) and Thaler (1999) who showed the limits of modern finance, which assumes that the study of substantially rational solutions to normative problems is a good basis for understanding real behavior. The focus on investors' behavior in the context of uncertainty is also at the center of the study by Hirschleifer (2015).

Overall, COVID-19 has left the question of investor behavior a nagging one. In a context of high uncertainty, both on asset prices and the prospects of economic recovery, and even on containment plans, the anticipation effects on future values raise real questions. Indeed, while a recent ongoing literature points to the impact of COVID-19 on stock markets, which appear sensitive to certain behavioral factors, the focus on COVID-19 and behavioral finance remains scarce. In addition, no previous study to our knowledge has simultaneously investigated stock market sensitivity to both macro-financial and behavioral factors in the context of COVID-19 pandemic. Our chapter aims to tackle the issue and to fill this gap.

3. Empirical Results

3.1 Data and Preliminary Analysis

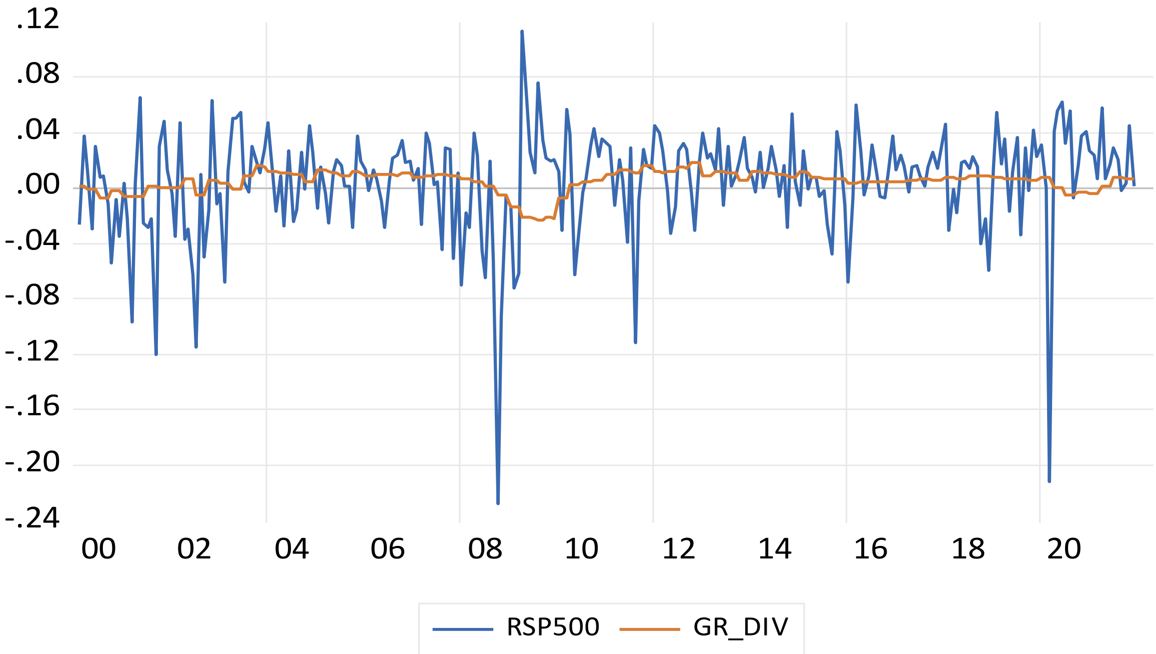
Our study investigates the dynamics of the US stock market both before and during the coronavirus pandemic. To this end, we used the S&P500, the largest US stock index. In order to specify its potential drivers, we retained three main classes of factors. The first class includes key financial variables: related dividends, related earnings, and total bond returns. While earnings and dividends constitute the benchmark fundamental drivers, the use of bond returns allowed us to capture further competition and arbitrage between risky and riskless financial assets. The second class includes more macroeconomic factors: inflation rate, unemployment rate, and long-term interest rate. The use of these factors enabled us to capture investors' reactions to announcements and news related to macroeconomic conjecture and monetary policy. The third class includes different types of behavioral factors: the Global Economic Policy Uncertainty Index (EPU) to assess for further uncertainty, the VIX index to capture investors' anxiety, the consumer/confidence sentiment index of the University of Michigan to capture investors' emotions, and the Equity Market Volatility -Infectious Disease Tracker index which allowed us to track the economic impact of the ongoing coronavirus pandemic and can be seen as a COVID-19 sensitivity index. The data is monthly and covers the period January 2000–December 2021, enabling us to examine the factors driving the US stock market dynamics both before and during the pandemic.

The data were gathered from different sources. The S&P500, dividend series, earning series, total bond returns, Consumer Price Index, and interest rate series came from the Robert Shiller Database. We obtained the other series (Economic and Policy Uncertainty index, VIX and the Infectious Disease Tracker Index from Fred of Saint Louis. Finally, the sentiment index is a measure of consumer confidence that we collected from the University of Michigan. Taking all these data into consideration enabled us to test US stock market behavior and reactions regarding macroeconomic, financial, and behavioral factors, including the disease exposure index. We also considered a dummy variable to precisely capture the various waves of the coronavirus pandemic. This variable takes the value zero from January 2000 to December 2019 and the value one from January 2020 to the end of the sample. The variable's construction is justified by the fact that the first COVID-19 case appeared in the US on 21 January 2020.

First, we checked for the presence of a unit root test in the data under consideration and performed the required transformation by applying the Box-Cox transformation to the following series: S&P500, dividends, earnings, VIX, Sentiment index, COVID-19-sensitivity index, and Uncertainty index in order to reduce their variances. We then applied two unit root tests (Augmented Dickey-Fuller (1979, 1981) tests and Philips-Perron (1988) tests) to check their stationarity in mean. Our results[1] showed the presence of a unit root in the S&P500, Dividends, Earnings, COVID-19-sensitivity index and sentiment index series, while the null hypothesis of non-stationarity was rejected for the other series. Accordingly, a first difference was computed for the non-stationary series, while the other series are used in level.

In order to compare the dynamics of the US stock price with its other drivers, we plotted the dynamics of the S&P500 returns and the growth rate of its dividends in Figure 1. Two interesting remarks can be made from this figure. First, the stock returns are more volatile than dividend growth rate, which is in line with Shiller (1981), and suggests that dividend policy changes are not enough to explain stock price variations. Second, given the smoothness inherent to dividend distribution, a dividend signal might only capture the cycle tendency, while failing to reproduce short-term price deviations. For example, dividends cannot capture the serious correction that characterized the US stock market during the global financial crisis and the coronavirus pandemic.

Figure 1. S&P500's Stock returns versus their dividends' growth rate



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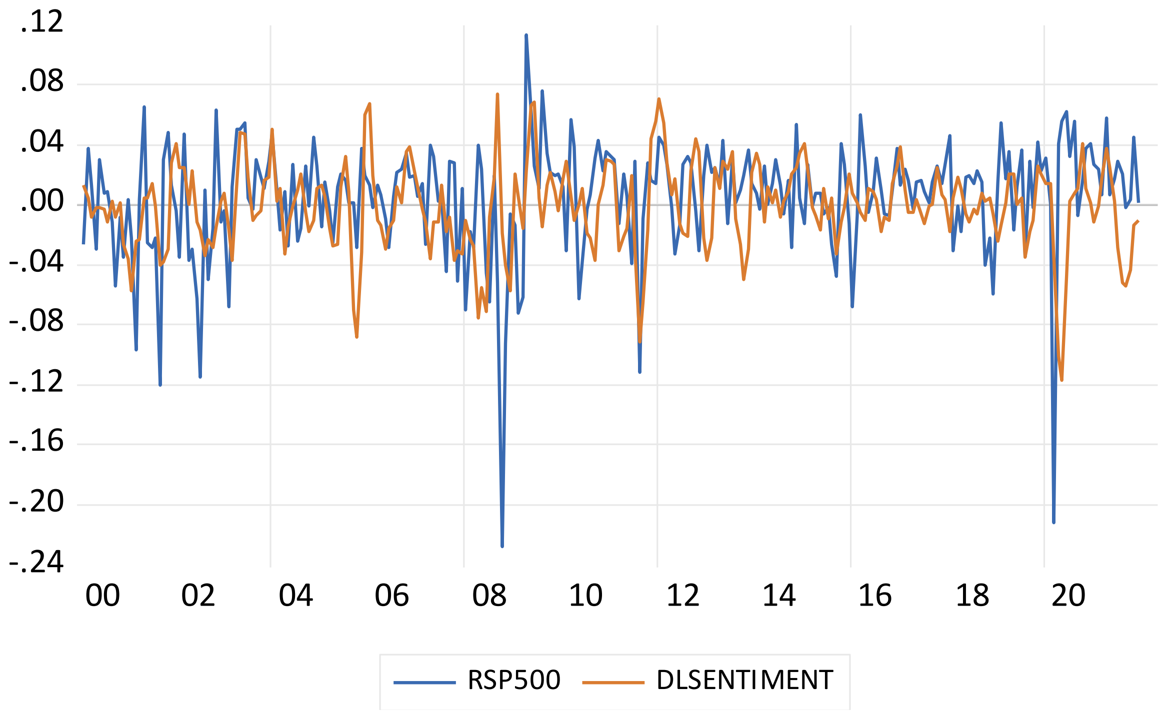
[1] To save space, we do not report the results of the unit root tests but the results are available upon request.

Note: RSP500 denotes the S&P500 stock returns. GR_DIV denotes the growth rate of the related dividends.

In order to check whether other factors might better explain these stock price deviations, we plot the US stock returns and sentiment index in Figure 2.

Figure 2. S&P500 stock returns versus sentiment index



Note: RSP500 denotes the S&P500 stock returns. DLSENTIMENT denotes changes in investor sentiment or confidence.

Three interesting results can be noted from Figure 2. First, unlike dividends, tracking changes in sentiments enabled us to reproduce short-term changes in stock prices, suggesting *a priori* evidence of sensitivity of the US stock market to investors' emotions. Second, we also noted the excess volatility of the sentiment index, suggesting further anxiety in investor behavior. Third, the effect of sentiment appears time varying, with changes in the sign and size. For example, interactions between the sentiment index and the US index during the global financial crisis differ from their interactions during the COVID-19 pandemic.

Next, we plotted the main descriptive statistics for US stock returns, dividends and earnings, and global bond returns in Table 1.

Table 1. Main descriptive statistics

	RSP500	GR_DIV	DLSENTIMENT	B_RETURNS
Mean	0.0045	0.0048	-0.0016	0.0100

Median	0.0118	0.0066	0.0000	0.0100
Maximum	0.1135	0.0185	0.0736	0.0110
Minimum	-0.2280	-0.0232	-0.1164	0.0094
Std. Dev.	0.0387	0.0077	0.0286	0.0001
Skewness	-1.9574	-1.5638	-0.4904	0.5349
Kurtosis	11.270	6.0016	4.6072	6.2634
Jarque-Bera (p-value)	917.46 (0.0000)	205.93 ((0.000)	38.850 (0.000)	129.25 (0.000)
Observations	263	263	263	263

Note: RSP500 denotes S&P500 stock returns and B_Returns denotes global bond returns. DLSENTIMENT denotes changes in investor sentiment or confidence. GR_DIV and GR_Earning denote the growth rate of related dividends and earnings respectively. DLSENTIMENT denotes changes in investors' sentiment or confidence. DLCOVID measures changes in the COVID-19 sensitivity index, and LEPU denotes the uncertainty index.

We, then, computed the matrix of unconditional correlations in order to get an overview of the linkages between US stock returns and the different financial, macroeconomic, and behavioral factors. We reported the main results in Table 2.

Table 2. Unconditional correlation matrix

	RSP500	**GR_DIV**	**GR_EARNING**	**DLSENTIMENT**	**DLCOVID**	**LEPU**	**B_RETURNS**
RSP500	1						
GR_DIV	-0.0023	1					
GR_EARNING	0.2896	-0.1383	1				
DLSENTIMENT	0.1821	-0.0167	0.1901	1			
DLCOVID	-0.1854	0.0392	-0.0172	-0.0259	1		
LEPU	-0.0197	-0.0721	-0.0977	-0.1041	0.0297	1	
B_RETURNS	-0.2552	0.0443	-0.1416	-0.0538	0.0771	-0.0346	1

Note: RSP500 denotes the S&P500 stock returns. DLSENTIMENT denotes changes in investors' sentiment or confidence. GR_DIV and GR_Earning denote the growth rate of related dividends and earnings respectively. DLSENTIMENT denotes changes in investors' sentiment or confidence. DLCOVID measures changes in the COVID-19 sensitivity index, and LEPU denotes the uncertainty index.

Table 2 indicates that while dividends are weakly correlated with the US stock index, its related earnings show a positive correlation. Further, an increase in investor confidence appears to have a positive impact on US stock returns, while uncertainty and COVID-19 show a negative linkage. In addition, there is a negative correlation between bonds and US stocks, suggesting further arbitrage between these two classes of financial assets.

3.2 Empirical Analysis

In order to analyze the dynamics of the US stock index, we regressed its stock returns on the three classes of factors (macro factors, financial factors, and behavioral factors) and ran different specifications. Formally, we first ran the following regression:

$$R_t = \alpha + \beta_1 GR\_DIV_t + \beta_2 GR\_EARNING_t + \varepsilon_t$$

where : R_t denotes the US stock return,
GR_DIV_t denotes the dividend growth rate,
$GR\_EARNING_t$ is the earning growth rate,
ε_t is an error term,
α, β_1 and β_2 are parameters.

(1)

We estimated model (1) and reported the main results in Table 3.

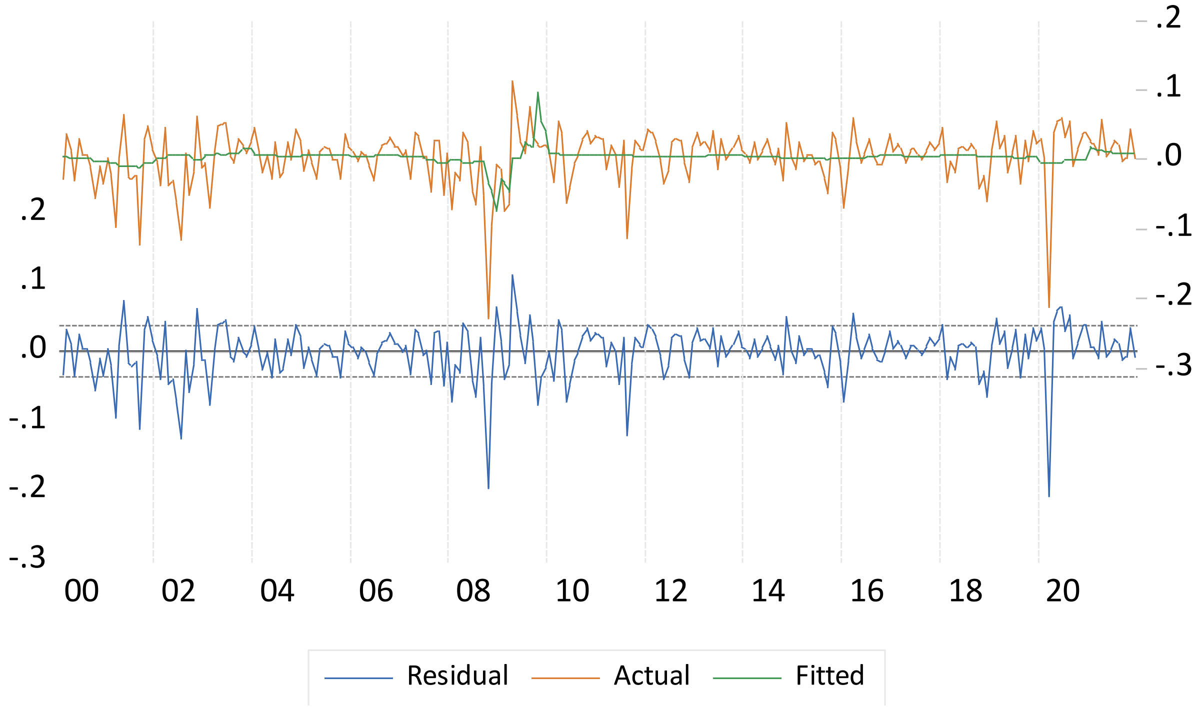
Table 3. Estimation results of model (1)

Variable	Estimators
C	0.002 (0.46)
GR_DIV	0.192 (0.64)
GR_EARNING	0.1402*** (0.00)
R^2	0.085
Log Likelihood	494.29
F-statistic	12.12 (0.00)
Durbin-Watson Statistics	1.74

Note: GR_DIV and GR_Earning denote the growth rates of related dividends and earnings respectively. C is a constant. R^2 is the determination coefficient. (***) denotes the significance at the 1% statistical level. Values in (.) denote the probabilities of the tests where HAC standard errors and covariances are corrected from heteroscedasticity and serial correlation using the Newey-West approach and a Bartlett Kernel with Newey-West fixed bandwidth = 5.00.

From Table 3, we can note that the effect of dividend growth is not significant, while an increase in earnings growth rate has a positive and significant effect on the dynamics of US stock returns. Overall, however, model (1) poorly explains the dynamics of US stock returns, suggesting that financial factors fail to explain the dynamics of the US stock market. Indeed, the R-squared does not exceed 8.5% and the Durbin-Watson test shows evidence of serial autocorrelation of one order. The weak quality of the model is confirmed by Figure 3 which indicates the importance of the unexplained part or estimation errors (residual). It is however important to recall that given the related autocorrelation problem, the analysis of significance of estimators should be carried out carefully.

Figure 3. Analyzing the performance of model (1)



Note: *Actual* denotes the observed US stock returns. *Fitted* refers to the estimated stock returns by model (1). *Residual* denotes the non-estimated part or the estimated errors of model (1).

We extended model (1) in order to improve it, introducing the following macroeconomic factors: interest rate, inflation rate, and unemployment rate, to better explain the US stock market dynamics. We thus specify model (2) as follows:

$$R_t = \alpha + \beta_1 GR\_DIV_t + \beta_2 GR\_EARNING_t + \beta_3 INTEREST\_RATE10_t + \beta_4 INF\_RATE_t + \beta_5 UNEMP\_RATE_t + \varepsilon_t$$

where : R_t denotes the US stock return,
$NTEREST\_RATE10_t$ denotes the interest rate,
INF_RATE_t is the inflation rate,
$UNEMP\_RATE_t$ is the unemployment rate,
ε_t is an error-term,
$\alpha, \beta_i \ \forall i = 1, \ldots, 5$ are parameters.

(2)

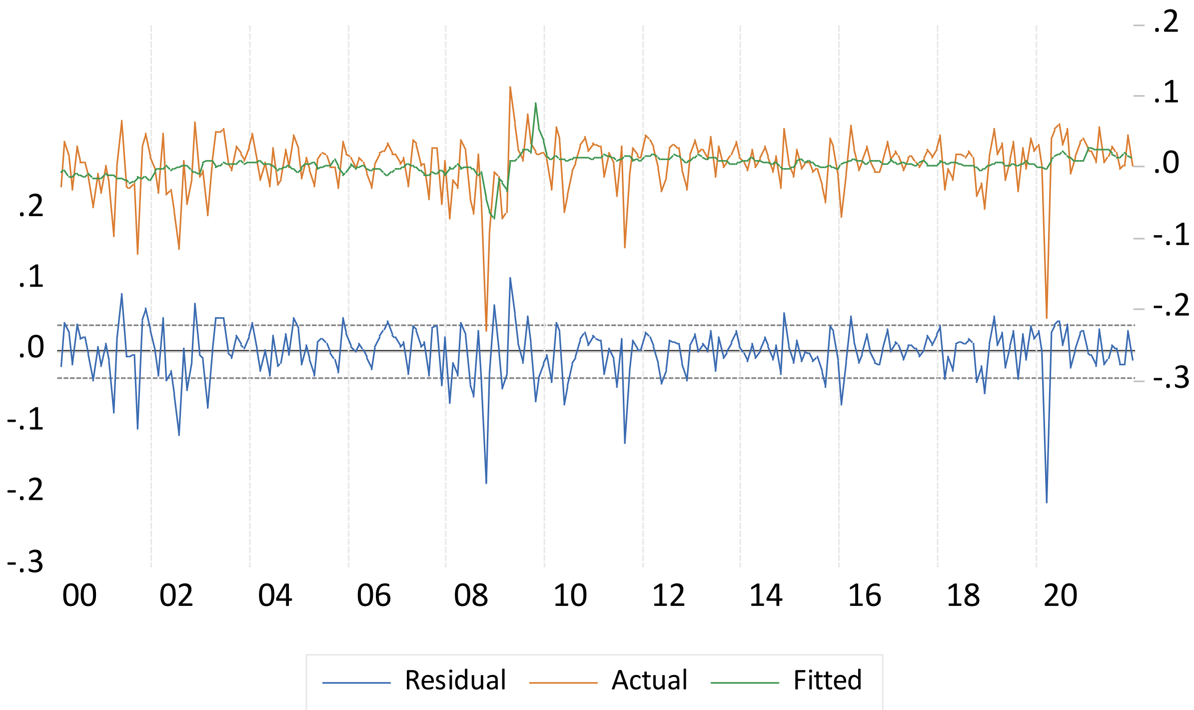
We estimated model (2) and reported the main results in Table 4. When considering model (2), the results remain the same as model (1) as dividends are not significant, while earnings still show a positive and significant effect. Further, the US stock market does not appear to react to changes in unemployment and inflation rates, while interest rate has a negative and significant effect. Indeed, our results suggest that an increase in interest rate by the central bank could reduce liquidity in the market and impact investor activity and trading. Overall, our specification improved slightly with regard to the log-likelihood function. However, as can be seen in Figure 4, the related estimated error is still high.

Table 4. Estimation results of model (2)

Variable	Estimators
C	0.004 (0.75)
GR_DIV	0.174 (0.641)
GR_EARNING	0.124*** (0.00)
INTEREST_RATE10	-0.404*** (0.01)
INF_RATE	1.057 (0.18)
UNEMP_RATE	0.166 (0.27)
R^2	0.12
Log Likelihood	500.01
F-statistic	7.29 (0.00)
Durbin-Watson Statistics	1.81

Note: GR_DIV and GR_Earning denote the growth rates of related dividends and earnings respectively. Interest_rate denotes the interest rate, while Inf_rate is the inflation rate and Unemp_rate refers to the unemployment rate. C is a constant. R^2 is the determination coefficient. (***) denotes the significance at the 1% statistical level. Values in (.) denote the probabilities of the tests.

Figure 4. Analyzing the performance of model (2)



Note: *Actual* denotes the observed US stock returns. *Fitted* refers to the estimated stock returns by model (2). *Residual* denotes the non-estimated part or the estimated errors of model (2).

Overall, it appears that even when considering both key financial variables and macroeconomic factors, our two previous specifications did not adequately reproduce the dynamics of the US stock index over the period 2000-2021. This is not unexpected when we recall that over the period under consideration, the market went through different episodes (subprime crisis in 2007, global financial crisis in 2008-2009, Greek public debt in 2012, COVID-19 in 2019-2020). Accordingly, the market experienced various changes, market states, and structural breaks. In addition, investors experienced different market situations that impacted their beliefs, behaviors, and investment strategies. In order to take all these parameters into account, we extended model (2) while introducing a set of behavioral variables and factors in addition to financial and macroeconomics factors. These behavioral factors include uncertainty, investor anxiety, and extra-fundamental variables related to the COVID-19 pandemic.

Accordingly, we tried different specifications with behavioral factors and retained the following model (3), defined as:

$$\begin{aligned} R_t &= \alpha + \beta_1 GR\_DIV_t + \beta_2 INTEREST\_RATE10_t + \beta_3 LEPU_t \\ &\quad + \beta_4 LVIX_t + \beta_5 DLSENTIMENT_{t-1} + \beta_6 DLCOVID_t + \varepsilon_t \end{aligned}$$

$where$: R_t denotes the US stock return,
$LEPU_t$ denotes the economic uncertainty in logarithm,
$LVIX_t$ is the VIX in logarithm,
$DLSENTIMENT_{t-1}$ measure changes in sentiment on $(t-1)$,
$DLCOVID_t$ measure changes in COVID-19 sensitivity index,
ε_t is an error term,
$\alpha, \beta_i \ \forall i = 1, \ldots, 6$ are parameters.

(3)

We estimated model (3) and reported the main results in Table (5). From Table (5), we noted that dividends now have a significant effect on stock returns, while interest rate still enters significantly and negatively. Interestingly, the VIX and the uncertainty indexes show negative and significant effects on US stock returns, indicating that greater uncertainty and anxiety might increase investor panic and provoke massive sales, inducing a stock return correction. Further, we found that COVID-19 news has a negative and significant impact on US stock returns, which suggests that the pandemic attenuated the US stock market performance. In addition, changes in investor confidence and sentiment may destabilize the dynamics of the US stock market. The impact of sentiment on US stock returns enters with one lag, suggesting further evidence of memory and persistence in the sentiment-US stock market relationship. Interestingly, the analysis of variance together with the analysis of Figure 5 led us to note that model (3) supplanted the first two specifications and improved the analysis of US stock returns, even if a serial correlation of order one still remains. The superiority of model (3) is confirmed through Figure 5, especially around the end of the period as the fitted series evolves in a similar way to the actual US stock return series. This finding is relevant and confirms the contribution of behavioral factors in explaining the dynamics of US stock returns.

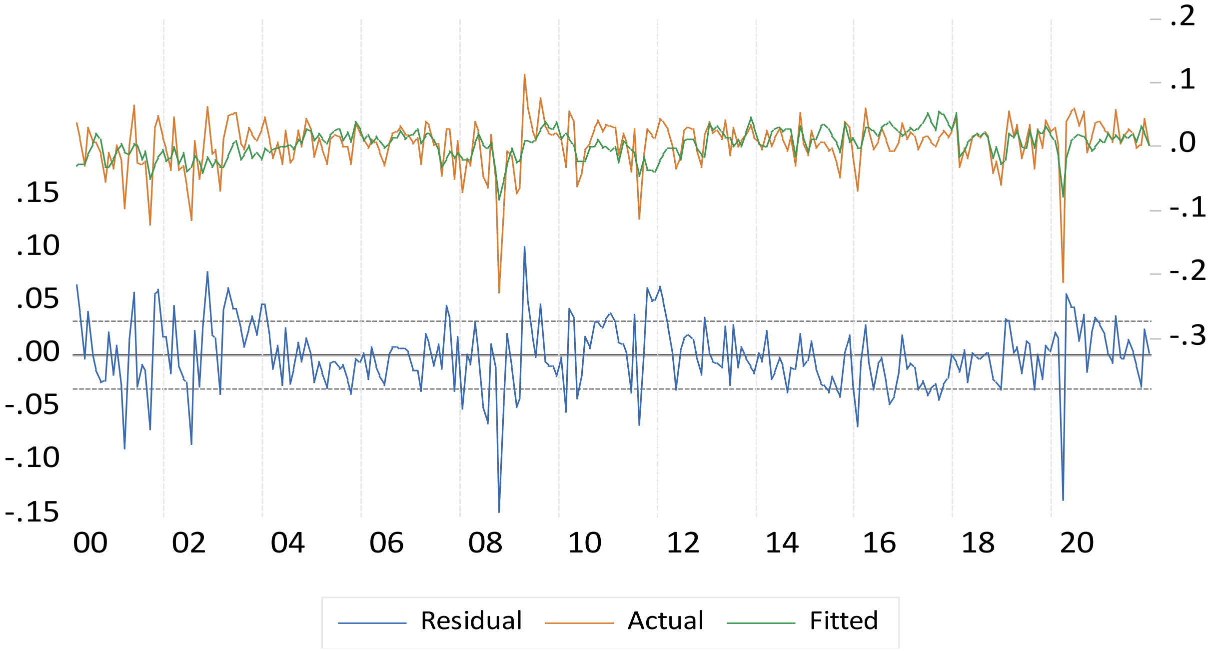
Table 5. Estimation results of model (3)

Variable	**Estimators**
C	0.276^{***} (0.00)

GR_DIV	-1.66*** (0.00)
INTEREST_RATE10	-0.831*** (0.00)
LEPU	-0.011* (0.10)
LVIX	-0.061*** (0.00)
DLSENTIMENT$_{t-1}$	-0.226** (0.05)
DLCOVID	-0.007*** (0.00)
R^2	0.33
Log Likelihood	532.78
F-statistic	20.82 (0.00)
Durbin-Watson Statistics	1.54

Note: GR_DIV denotes the growth rate of related dividends. Interest_rate denotes the interest rate, while LEPU and LVIX refer to the logarithms of uncertainty and VIX indices respectively. DLSENTIMENT tracks changes in investors' sentiment and confidence, whereas DLCOVID measures changes in the COVID-19 sensitivity index. C is a constant. R^2 is the determination coefficient. (***), (**) and (*) denote the significance at the 1%, 5% and 10% statistical level respectively. Values in (.) denote the probabilities of the tests.

Figure 5. Analyzing the performance of model (3)



Finally, in order to take this persistence into account and also to re-parameter our model to consider the structural breaks induced by the global financial crisis of 2008-2009 and the COVID-19 shock, we extended model 3 in a nonlinear context. To this end, we first applied the structural break tests of Bai-Perron (2003), which examines the null hypothesis of no-structural breaks against the alternative hypothesis of a structural break. In practice, the test allows for a maximum of five breaks and, interestingly, the structural breaks as well as the threshold are specified endogenously. The main results are reported in Table 6. From this table, we noted the presence of just one break, suggesting that under the alternative hypothesis, we should build a two-regime model and that the threshold variable that conducts the switch between the two regimes corresponds to the LVIX variable.

Table 6. Results of the structural break test

Sequential F-statistic determined thresholds: 1

Threshold Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1 *	14.91253	104.3877	21.87
1 vs. 2	2.347382	16.43167	24.17

* Significant at the 0.05 level.

** Bai-Perron (Econometric Journal, 2003) critical values.

Threshold values :

	Threshold	Threshold Variable
1	3.282074	LVIX

Accordingly, we specify the two-regime regression for US stock returns as follows:

$$R_t = \left\{ \begin{array}{c} (\alpha_1 + \beta_{11} GR\_DIV_t + \beta_{21} INTEREST\_RATE10_t + \beta_{31} LEPU_t + \\ +\beta_{41} LVIX_t + \beta_{51} DLSENTIMENT_{t-1} + \beta_{61} DLCOVID_t + \varepsilon_{1t}) \text{ if } LVIX_t < \tau \\ (\alpha_2 + \beta_{12} GR\_DIV_t + \beta_{22} INTEREST\_RATE10_t + \beta_{32} LEPU_t + \\ +\beta_{42} LVIX_t + \beta_{52} DLSENTIMENT_{t-1} + \beta_{62} DLCOVID_t + \varepsilon_{2t}) \text{ if } LVIX_t \geqslant \tau \end{array} \right\} \tag{4}$$

where : R_t denotes the US stock return,

$LEPU_t$ denotes the economic uncertainty in logarithm,

$LVIX_t$ is the VIX in logarithm,

$DLSENTIMENT_{t-1}$ measure changes in sentiment on $(t-1)$,

$DLCOVID_t$ measure changes in COVID-19 sensitivity index,

$\varepsilon_{jt}\ \forall j = 1,2$ is an error term for the regime j,

$\alpha_j, \beta_{ij}\ \forall i = 1,\ldots,6,\ \forall j = 1,2$ are parameters.

τ denotes the threshold parameter.

We estimated model (4) by the nonlinear least square method using the estimators of the linear model as initial values, and we reported the main results in Table 7.

Table 7. Estimation results of model (4)

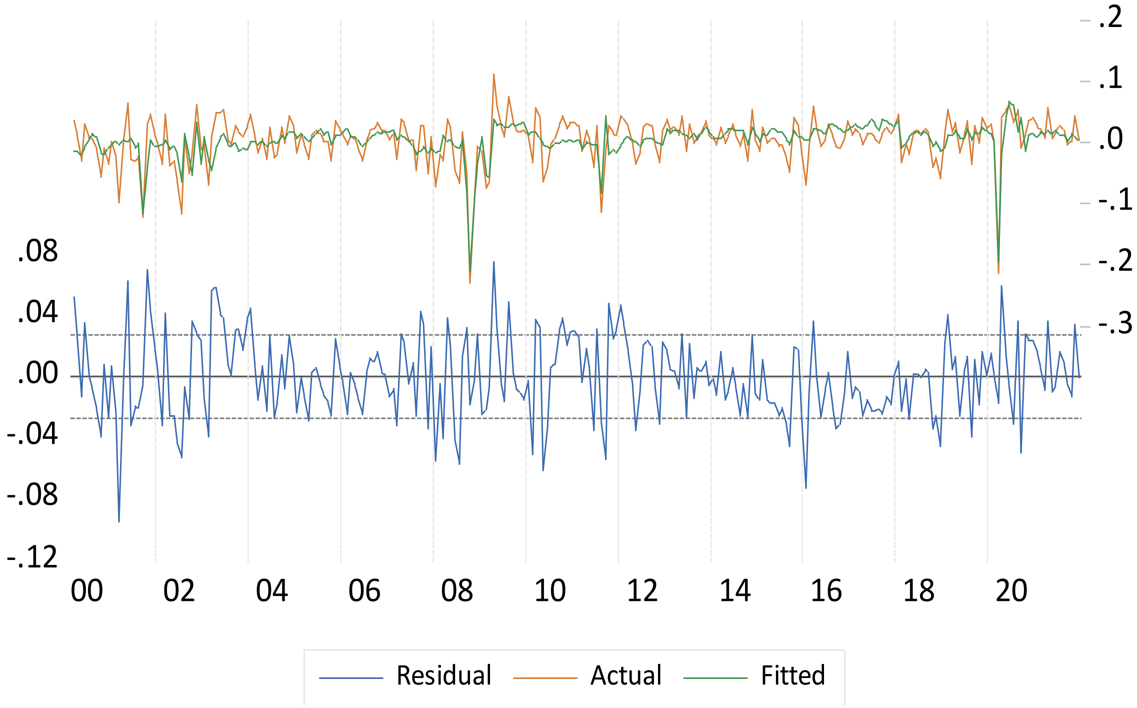
Variable	**Regime 1**	**Regime 2**
C	0.182*** (0.00)	0.996*** (0.00)
GR_DIV	-1.302*** (0.00)	-1.949*** (0.00)
INTEREST_RATE10	-0.564*** (0.00)	-2.593*** (0.00)
LEPU	-0.005 (0.43)	-0.072*** (0.00)
LVIX	-0.042*** (0.00)	-0.165*** (0.00)
DLSENTIMENT$_{t-1}$	0.004 (0.95)	-0.641*** (0.05)
DLCOVID	-0.003 (0.12)	-0.039*** (0.00)
τ	3.282	
R^2	0.53	
Log Likelihood	578.80	
F-statistic	21.31 (0.00)	
Durbin-Watson Statistics	1.70	

Note: GR_DIV denotes the growth rate of related dividends. Interest_rate denotes the interest rate, while LEPU and LVIX refer to the logarithms of uncertainty and VIX indices respectively. DLSENTIMENT tracks changes in investors' sentiment and confidence, while DLCOVID measures changes in the COVID-19 sensitivity index. C is a constant. R^2 is the determination coefficient. (***), (**) and (*) denote the significance at the 1%, 5%, and 10% statistical level respectively. Values in (.) denote the probabilities of the tests. τ is the threshold parameter.

From Table 7, several interesting results can be noted. First, dividend growth rate and interest rate have a significant effect on US stock returns. Whatever the regime under consideration, their effects, in absolute value, are higher in the second regime than in the first regime. Second, while the VIX has a negative but close to zero effect on US stock returns in the first regime, the US stock market appears less sensitive to uncertainty, COVID-19 news, and investor sentiment in the first regime. This suggests that in the first regime, when the VIX is relatively low and less than 26.62, the US stock market is driven more by financial and macroeconomic factors, especially dividends and interest rate. Third, in the second regime, when VIX starts taking high value, the US stock market become negatively and significantly sensitive to the level of economic uncertainty. Further, the effect of VIX that reflects investors' anxiety becomes significantly high and attains more than four times its impact in the first regime on US stock returns.

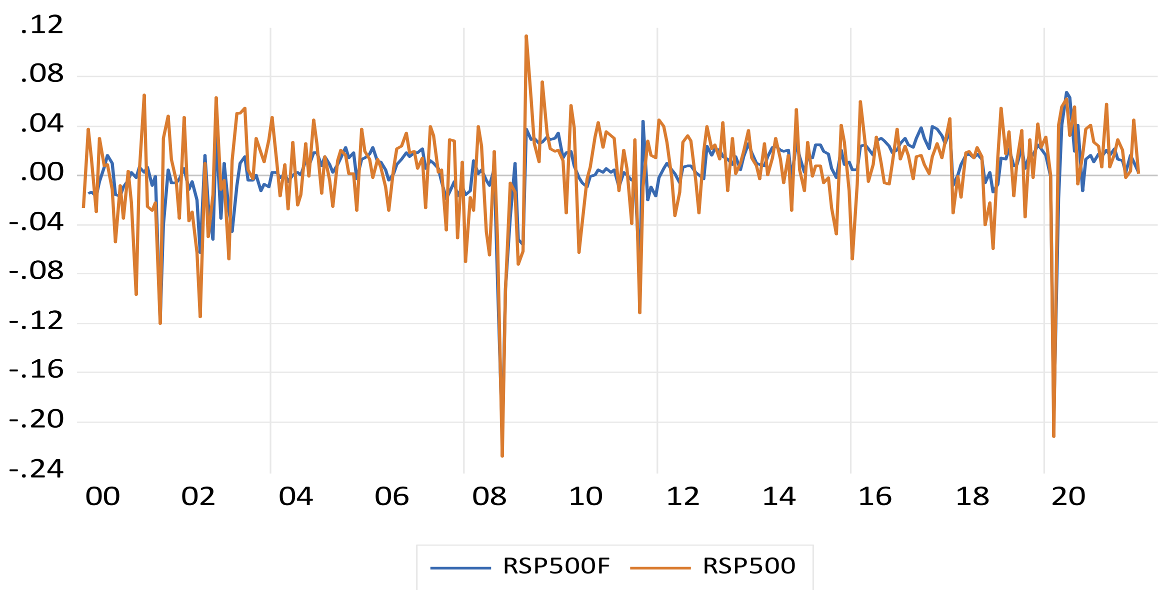
In addition, in the second regime, the US stock market reacts negatively and significantly to COVID-19 news and changes in investor sentiment. Overall, this nonlinear specification supplants the first three linear models and improves the analysis of US stock market dynamics. In particular, it contributes by identifying two regimes. In the first regime, the market is most likely driven and governed by financial and macro factors, while in the second regime, it is driven by both financial and behavioral factors. Consideration of nonlinearity and the flexibility achieved by combining financial, macroeconomic, and behavioral factors improved the modeling process, enabling us to reproduce the dynamics of US stock returns, notably during the global financial crisis and the COVID-19 downturn (Figure 6).

Figure 6. Analyzing the performance of model (4)



In the last step, we double checked the forecasting performance of our nonlinear model. To this end, we computed in-sample forecasts. The analysis of these forecasts, reported in Figure 7, shows that our two-regime model effectively reproduces the dynamics of US stock returns, especially during the global financial crisis (2008) and the COVID-19 pandemic, highlighting the interest of including information about behavioral factors (uncertainty, sentiment) and COVID-19 news to forecast US stock returns.

Figure 7. Results of in-sample forecasts



Note: RSP500 denotes the observed US stock returns. RSP500F measures the in-sample forecasts of US stock returns.

The forecasting performance of the non-linear model can also be appreciated when analyzing the forecast tests reported in Table 8. Indeed, overall, these tests indicate a good forecasting performance of our nonlinear specification.

Table 8. Forecasting evaluation of model (4)

Root Mean Squared Error	0.026566
Mean Absolute Error	0.021255
Theil Inequality Coef.	0.394207
Bias Proportion	0.000000
Variance Proportion	0.158470
Covariance Proportion	0.841530
Theil U2 Coefficient	0.146822
Symmetric MAPE	115.4915

4. Conclusion

This chapter analyses the dynamics of the US stock market (S&P500) in times of COVID-19. In particular, we assess the contribution of various drivers (fundamentals, behavioral factors, etc.) to better explain the high of volatility of the US stock market both before and during the COVID-19 pandemic. To this end, we relied on recent financial, behavioral, and macroeconomic data obtained from different sources, applying several linear and nonlinear time series tests. Accordingly, we show that US stock returns are driven by both macro-financial and behavioral factors. In particular, we built a two-regime multifactorial model that reproduces the dynamics of the US market in which financial factors play a key role whatever the regime, while the action of behavioral factors appears more significant only in the second regime when investors' anxiety exceeds a given threshold. Finally, our in-sample forecasts show the superiority of our nonlinear multifactorial model to forecast the dynamics of the US stock market.

It is however important to mention that given that the residuals of our model always showed a high autocorrelation, which can affect the efficiency of our estimators, it would be relevant to extend our specification while correcting for this autocorrelation. To this end, it would be possible to parameter an ARDL model, through the introduction of lagged variables and to re-estimate the effects of behavioral factors on the US stock returns. This point might be a natural future extension for this study.

References

Albulescu, C.T., (2021), COVID-19 and the United States financial markets volatility, *Finance Research Letters*, 38, January.

Apergis, E., & Apergis, N. (2021). Inflation expectations, volatility and Covid-19: evidence from the US inflation swap rates. *Applied Economics Letters*, *28*(15), 1327-1331.

Ashraf, B. N., & Goodell, J. W. (2021). COVID-19 social distancing measures and economic growth: Distinguishing short-and long-term effects. *Finance Research Letters*, December, 102639.

Bai, J. and Perron P. (2003), Computation and Analysis of Multiple Structural Change Models, *Journal of Applied Econometrics*, 18 (1), 1-22.

Bandopadhyaya A., and Truong D. (2010) Who Knew: Financial Crises and Investor Sentiment. Working Paper. University of Massachusetts Boston. ScholarWorks at UMass Boston.

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The review of asset pricing studies*, 10(4), 742-758.

Bansal, T. (2020). Behavioral finance and COVID-19: cognitive errors that determine the financial future. *Available at SSRN 3595749*.

Bourghelle, D., Jawadi, F., & Rozin, P. (2022). Do collective emotions drive bitcoin volatility? A triple regime-switching vector approach. *Journal of Economic Behavior & Organization*, *196*, 294-306.

Cappelle-Blancard, G., Desroziers A. (2020) The Stock Market Is not the Economy? Insights from the COVID-19 Crisis ***CEPR Covid Economics, 2020.***

Chundakkadan, R. and Nedumparambi, E. (2021). In search of COVID-19 and Stock Market behavior, *Global Finance Journal*, 100639.

De Bondt, W. F., & Thaler, R. H. (1995). Financial decision-making in markets and firms: A behavioral perspective. *Handbooks in operations research and management science*, *9*, 385-410.

Dickey. 0. A., and Fuller, W. A. (1979), Distribution of the Estimators for Autoregressive Time Series with a Unit Root, *Journal of the American Statistical Association*, 74. 421-431.

Dickey, 0. A., and Fuller, V. A. (1981), Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root, *Econometrica*, 49(4), 1057-1072.

Goldstein, I., Koijen, R., Mueller, H. M., (2021), COVID-19 and its impact on financial markets and the real economy, *The Review of Financial Studies*, 34(11), 5135–5148.

Gormsen, N. and Koijen, R. (2020), Coronavirus: impact on stock prices and growth expectations, *Working Paper n°2020-22*, University of Chicago, Booth Friedman Institute for Economics.

Hirshleifer, D. (2015). Behavioral finance. *Annual Review of Financial Economics*, *7*, 133-159.

Igan, D., Kirti, D., Perioa, S., M. (2020). The disconnect between financial markets and the real economy, *IMF Research. Special note series* on COVID-19.

Landier, A. & D. Thesmar. (2020). Earnings Expectations during the COVID-19 Crisis *The Review of Asset Pricing Studies*, Volume 10, Issue 4, December, Pages 598–617

Lee, H. (2020). Exploring the Initial Impact of COVID-19 Sentiment on US Stock Market Using Big Data, *Sustainability*, 12(6).

Mazur, M., Dang, M. and Vega, M. (2021). COVID-19 and the March 2020 stock market crash. Evidence from S&P 500. *Finance Research Letters*, 38.

Meyer, B. H., Prescott, B., & Sheng, X. S. (2022). The impact of the COVID-19 pandemic on business expectations. *International Journal of Forecasting*, *38*(2), 529-544.

Ortmann, R., Pelster, M., & Wengerek, S. T. (2020). COVID-19 and investor behavior. *Finance research letters*, *37*, 101717.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2), 335-346.

Sergi, B. S., Harjoto, M. A., Rossi, F., & Lee, R. (2021). Do stock markets love misery? Evidence from the COVID-19. *Finance Research Letters*, *42*, 101923.

Shiller, R. J. (2001). Exuberant reporting. *Harvard International Review*, *23*(1), 60-6

Subramaniam, S., & Chakraborty, M. (2021). COVID-19 fear index: does it matter for stock market returns?. *Review of Behavioral Finance*. 13(1), 40-50.

Thaler, R. H. (1999). The end of behavioral finance. *Financial Analysts Journal*, *55*(6), 12-17.

Vasileiou, E. (2021). Behavioral finance and market efficiency in the time of the COVID-19 pandemic: does fear drive the market?. *International Review of Applied Economics*, *35*(2), 224-241.

Yu, X., Xiao, K. and Liu, J. (2022). Dynamic co-movements of COVID-19 pandemic anxieties and stock market returns, *Finance Research Letters*, 46, Part A.