Impact of the COVID-19 pandemic on the relationship between uncertainty factors, investor behavioral biases and the stock market reaction of US Fintech companies

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Abstract

Object: This article investigates the impact of the COVID-19 pandemic on the relationship between uncertainty factors (Equity Market Volatility–Infectious Diseases, Economic Policy Uncertainty and Financial Stress) and investor behavioral biases (Herding Behavior, Loss Aversion, Mental Accounting and Overconfidence) with the US Fintech stock market abnormal returns.

Methodology: we analyze this relationship by using Johansen cointegration test, Granger causality test and the Ordinary least square method for the period from July 20, 2016 to December 31, 2021.
Results: The Empirical results indicated the presence of a long-run equilibrium relationship between all the studied variables, before and during the COVID-19 pandemic period. In fact, the obtained results indicated that the COVID-19 pandemic is a crucial source for resulting abnormal returns in the US Fintech market. Especially, during the COVID-19 pandemic, the Fintech market under-reacted to the common signal of financial stress. Moreover, behavioral biases, especially, overconfidence and herding, have a power positive effect on the abnormal reaction of US Fintech stock market, comparatively to the pre COVID-19 period.
Originality: This study is one of the few studies which have compared the effect of uncertainty factors and the investor's behavioral biases on the US Fintech stock market reaction before and during the COVID-19 pandemic.

Keywords: Fintech; COVID-19; uncertainty factors; investor behavioral biases, stock market reaction, Ordinary least squares method.

L’impact de la pandémie de COVID-19 sur la relation entre les facteurs d'incertitude, les biais comportementaux des investisseurs et la réaction boursière des Fintech américaines

Résumé

Objectif : Le but de l’étude est d’identifier l’impact de la pandémie COVID-19 sur la relation entre les facteurs d’incertitudes (volatilité des marchés boursiers -maladies infectieuses, incertitude de la politique économique et le stress financier) et les biais comportementaux des investisseurs (le comportement grégaire, l’aversion aux pertes, la comptabilité mentale et l’excès de confiance) avec les rendements anormaux du marché Américain de la Fintech.
Méthode : Pour parvenir à cet objectif, cet article fait recours au test de cointégration de Johensen, test de causalité de Granger et méthode des moindres carrés ordinaires pour la période allant du 16 Juillet 2016 au 31 décembre 2021.
Résultats : Les résultats obtenus démontrent qu’il existe une relation à long terme entre les variables étudiées avant et durant la période de la pandémie COVID-19. En fait, ces résultats indiquent que cette pandémie est une source cruciale pour résulter des rendements anormaux dans le marché boursier américain de la Fintech. En particulier, pendant l’épidémie de COVID-19, le marché Fintech a sous-réagi au signal commun de stress financier. De plus, les biais comportementaux, en particulier l'excès de confiance et le comportement grégaire, ont un effet positif sur la réaction anormale du marché boursier américain de la Fintech, comparativement à la période avant COVID-19.
Originalité/ Pertinence: Cette étude est l'une des rares études qui ont comparé l’effet des biais comportementaux et des facteurs d'incertitude sur la réaction du marché américain de la Fintech avant et pendant la pandémie COVID-19.

Mots clés : Fintech ; COVID-19 ; facteurs d'incertitudes; biais comportementaux des investisseurs, réaction des marchés boursiers, méthode des moindres carrés ordinaires.

1. Introduction

In the aftermath of the global financial crisis (GFC) of 2008, the world of finance had undergone a tremendous change as technology created new paradigms. However, financial technology (Fintech) is a relatively new concept defined as the evolution of the interaction between technology and traditional financial services (Lee et al., 2018).

Due to the outbreak of the COVID-19, investors changed their preferences about the use of Fintech services, which are more transparent and less liquid than the traditional ones (Sindreu, 2020). Although the COVID-19 was an exceptional several shock to the economy and financial markets, and caused various uncertainties that give rise to excessive financial stock market volatility, it created opportunities for the US Fintech industry due the quarantine and social distancing. Therefore, it is important to analyze the dynamics of the stock markets in periods of extreme co-movements with other factors based on uncertainty. In fact, numerous papers examined the relationship between uncertainty factors and the stock market volatility, especially in turbulent events. For example, Baker et al. (2019) studied the impact of the COVID-19 on the volatility of the U.S. stock market, which is more significant than any other infectious disease outbreak. In addition, given the highly uncertain economic policy due to the spread patterns and the unknown future situation of the Coronavirus, cash flows are very unlikely to weather the crisis, leading to the depreciation of the stock markets (Azimli, 2020; youssef et al. 2021; Trichilli et al. 2020; Trichilli and Abbes, 2022). Also, Dai et al. (2021) examined the impact of Economic Policy Uncertainties on the crash risk of US stock market during the COVID-19 pandemic. In this vein, Floros et al. (2021) found an extreme high financial uncertainty and varying expectations of losses in the US financial markets that can be associated with a high level of financial stress.

The dynamic relation between the stock market reaction and the COVID-19 uncertainty may lead to a shift of the investor's behavior. Therefore, investors overreact to any available information that can cause the deviation of efficient market theory and the fluctuation of the stock market. Previously, Kahneman and Tversky (1982) suggested that in experimental asset markets, investors overreact to new information with enthusiasm or excessive fear. Hence, behavioral finance attempts to explain how investors make their decisions, or better yet, the irrationality behind them. As for Nair and Antony (2015) they do not see behavioral finance as a substitute for classical finance theories but as a means of understanding irrational investor's behavior and the causes of the market's sudden rise or fall. Ahmad et al. (2017) indicated that the investor's behavior determines how asset prices and the stock market change. In this context, Mushinada (2020) analyzed the investors' differential reaction to information at market level, contribution of their confidence level and adaptive behavior to excessive market volatility in Indian stock market.

Moreover, many studies have confirmed the direct relationship between herd behavior and dynamic conditional volatility in the US stock market (BenSaïda et al. 2015; Litimi et al. 2016; BenSaïda 2017; Choi and Yoon, 2020; Fei and Liu, 2021; Trichilli et al. 2020; Trichilli et al. 2021). According to Barberis and Huang (2001), loss aversion behavior could make stock prices cause abnormal returns resulting in a stock market reaction leading to variations in returns. Furthermore, in financial markets, some researchers, such as Metwally and Darwish (2015) showed that price volatility is necessarily due to the excessive investor's confidence

In this background, the main objective of this paper is to investigate the impact of the COVID-19 pandemic on the relationship between uncertainty factors (Economic Policy Uncertainty, Equity Market Volatility–Infectious Diseases, Financial Stress) and the investor's behavioral biases (overconfidence, herding, mental accounting and loss aversion) with the US Fintech stock market abnormal returns. To achieve this purpose, we use the Johansen co-integration test to examine the long term relationship between uncertainty factors, the investor's behavioral biases and the stock market reaction of listed Fintech companies in the USA. Then, the Granger causality test is applied to analyze the causality dynamics between these variables. Finally, the simple Ordinary Least Squares (OLS) regression is used to study the relationship between all the studied variables based on the conditional mean functions.

Recently, many studies, namely those of (Arun and Ozili, 2020; Bouri et al. 2020; Trichilli et al. 2018; Souissi et al. 2020) have focused on the impact of the COVID-19 on the financial stock markets. However, there is insufficient evidence concerning at which point this pandemic can be a generator of many instabilities that can result in an extreme connection between the dynamic of the stock markets and uncertainty factors and then, a turbulence in the behavior of investors. From this perspective, the study of this relationship has a crucial effect on the stability of the stock markets.
Thus, the contribution of this paper is threefold. First, it investigates the reaction of the US Fintech industry to the outbreak of the COVID-19 crisis. Moreover, this investigation is of great importance since the COVID-19 crisis continues to generate uncertainty, and many Fintech firms are under stress. Second, this paper contributes to widening the scope of the behavioral finance literature by integrating the investor's behavioral biases to investigate the dynamics of the US Fintech stocks. Third, this paper compares the effect of uncertainty factors and the investor's behavioral biases on the US Fintech stock market reaction before and during the COVID-19. Subsequently, examining this association before and during such pandemic period can be helpful to investors and portfolio managers, who are facing various difficulties about capturing good strategies during the COVID-19, in order to deeply explain the factors that most affect the dynamic of the Fintech stock market.
For this reason, the layout of the paper is as follows. Section 2 presents the literature review then, section 3 describes the data and methodology, section 4 presents the empirical research and the obtained results and finally, section 5 offers some concluding remarks.

2. Literature review

There are numerous papers dealing with the existence of different factors that affect the reaction of financial stock markets. In this vein, the Equity Market Volatility-Infectious Diseases Tracker is the outcome of a study by Baker et al. (2020) aimed to measure the magnitude of infectious diseases, especially, the predominance of the infectious COVID-19 pandemic in equity Market. In fact, Bai et al. (2020) used this index to analyze the effects of infectious diseases on the volatility of the stock markets in the USA, UK, Japan, and China. Their findings indicated a strong relationship between them. According to Haroon and Rizvi (2020), the COVID-19 caused greater volatility in stock, gold and crypto-currency markets than in the normal days. However, Schell et al. (2020) showed that the COVID-19 pandemic negatively affected the abnormal returns of the majority of the stock markets while this phenomenon did not exist in the remaining, such as Ebola, and the Zika virus. For their part, Baker et al. (2016) measured the economic policy uncertainty (EPU) to check if it may affect the stock market returns, especially in the period of crisis (Abbes and Trichilli, 2015; Hu et al., 2018; Balcilar et al.,2019 ; Christou et al., 2020; Trichilli et al. 2020). In this context, many studies has examined the effect of the economic policy uncertainty on the relationship between financial assets, including those between the stock markets (Li and Peng, 2017), bonds and stocks (Fang et al., 2017), commodity and equity markets (Badshah et al., 2019), as well as the Bitcoin and conventional assets (Matkovskyy et al., 2020). Additionally, Yu and Huang (2021) analyzed the effect of Chinese economic policy uncertainty on stock volatility and they found a significant impact. Furthermore, financial stress is considered as a state of financial instability and it is largely dominated by price-related indicators, such as the stock prices, which are associated with other indices, namely the financial fragility index (Bagliano and Morana, 2014) and the financial security index (Jia and Li, 2015; Matkovskyy et al., 2016). Recently, Gkillas et al. (2020) have employed financial stress index to forecast the realized volatility of oil price markets from 2000 to 2017 in the USA and other economies. The results revealed that financial stress has an important implication in the forecasting of oil price volatility.

In addition, Daniel and Hirshleifer (2015) analyzed the linkage between the investor's behavior and the market volatility and they that showed that irrational investors destabilize the prices when buying, especially when prices are high and selling, when they are low. Furthermore, herding behavior is a major cause of speculative bubbles and extreme risk-levels since the measure of volatility is positively affected by the presence of this bias (Hilliard and Zhang, 2015). More recently, Chang et al. (2020) investigated the impact of herding behavior in the case of the USA, European and Asian energy stock returns from 2000 to 2020. Their main results indicated that herding behavior is more apparent in extremely high returns, especially, after the global financial crisis. In fact, loss aversion is the tendency of investors to be more sensitive to losses than to gains, making them reluctant to sell any investment that could result in a loss (Doviak, 2016 ; Jordan et al., 2015; Trichilli et al. 2020). For their part, Easley and Yang (2015) indicated that investors subject to loss aversion bias do not affect the market price. However, Yang (2019) indicated that loss aversion has a significant impact on financial markets. Following this, Tariq and Ullah (2013) found a significant positive effect of an investor's excessive confidence on the reaction of the stock markets. Mushinada and Veluri (2018) analyzed the overconfidence hypothesis at Bombay Stock Exchange and they showed that the excessive trading of overconfident investors give rise to the observed excessive volatility. In this vein, Boussaidi (2020) affirmed the crucial impact of overconfidence as he detected a high volatility in the MENA stock markets when the levels of private information are rising.

3. Data and methodology

3.1. Data and variables definition

In this study, we used a sample of 48 companies created in KBW Financial Technology: KFTX index during the full period from 20/07/2016 to 31/12/2021.We have used the test of Chow (1960) to identify the breakpoint dates. Based on this test, we have divided the sample period into two sub-periods; before the COVID-19 crisis, (from 20/07/2016 to 31/12/2019), and during the COVID-19 crisis (from 01/01/2020 to 31/12/2021).
The EPU and EMV-ID indices are taken from the Economic Policy Uncertainty index. However, FS, as well, which is the data necessary to measure the investor's behavior biases and the abnormal returns of Fintech stock market are extracted from the DataStream THOMSON RETEURS database.
In this paper, we used dependent and independent variables.

3.1.1. The dependent variable

Regarding to the dependent variable, we used the abnormal returns (AR) proxy to measure the dynamic of the US Fintech stock market. This variable is measured as follows:

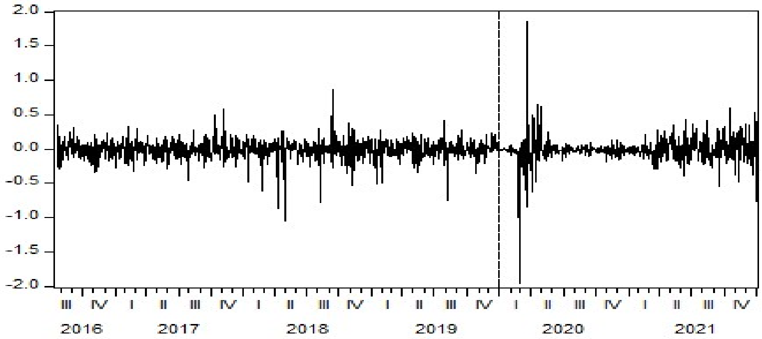
$$AR_{i,t} = R_{i,t} - R_{m,t} \qquad (1)$$

Where $\mathrm{R}_{\mathrm{i,t}}$ presents the Real return observed of the KFTX Index containing 48 companies;$R_{m,t}$ presents the average returns of all equities[23]. This expression means that the abnormal return is equal to the difference between the profitability of stock *i* and the Fintech market returns.

Figure 1 depicts the daily evolution of Fintech stock market return. Obviously, the Fintech stock market returns reflect turbulent economic events such as the COVID-19 crisis when the return hits historic lowest points.

[23]There is no risk adjustment except for movements in the market as a whole and the adjustment was the same for all stocks (De Bondt et Thaler, 1985).

Figure 1.*Daily Fintech stock market reaction*



3.1.2. The independent variables

For the independent variables, we used the uncertainty factors (Economic Policy Uncertainty index (EPU), the Equity Market Volatility – Infectious Diseases (EMV-ID)) and the behavioral biases (herding behavior (HB), loss aversion (LA), mental accounting (MA) and overconfidence (OC). These variables are defined as follows:

The Economic Policy Uncertainty index is proposed by Baker et al. (2016) and it is based on daily newspapers in the United States From 1985 to 2021.

*The Equity Market Volatility – Infectious Diseases*is proposed by Baker et al., (2019) and it is based on daily Infectious Disease (epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1) Equity (economic, economy, financial) Market (stock market", equity, equities, "Standard and Poors") Volatility (volatility, volatile, uncertain, uncertainty, risk, risky)Tracker. This daily measure is available from January 1985 to present.

The Financial Stress index (FSI) was developed in the St. Louis Fed Stress Index (Kliesen and Smith 2010) and it is based on the instability of stock markets in the periods of high uncertainties. It attempts to measure the financial market stress by combining many indicators into a single index that becomes a composite measure of US financial market stress.

The Herding behavior is calculated by the following expression (Thirikwa and Olweny, 2015)

$$CSADt = \frac{1}{N}\sum_{i=1}^{N} |r_{i,t} - r_{m,t}| \qquad (2)$$

Where$r_{i,t}$presents the stock market return observed in company i during period$t$; $r_{m,t}$presents the average cross-sectional return in month t (the average market return). The expression CSAD means that dispersions would decrease or at least increase at a less proportional rate with the return of the market.

The Loss Aversion is measured (Barberis and Huang, 2001) as follows:

$$X_{i,t+1} = S_{i,t}R_{it+1} - S_{i,t}R_{f,t} \qquad (3)$$

Where$X_{i,t+1}$ presents the measures of the gain or loss on stock i between time $(t-1)$ and time t; $S_{i,t}$ presents the reference price of share i at time t; R_{it+1} represents the expected future return; $R_{f,t}$ presents the risk-free rate (Treasury bill rate). The gain was equal to the value of stock i at time $(t + 1)$ minus its value at time t multiplied by the risk-free rate.

The Mental Accounting is measured (Barberis and Huang, 2001) by the following formula :

$$K = \frac{P_0}{D_0} (4)$$

P_0isthe price of the stock; $D_0$is the dividend paid in this day.

$$SMR = Portfolio\ A\ -\ Portfolio\ B \qquad (5)$$

Where *Portfolio A* is the companies with low ratios; *Portfolio B* presents companies with a high ratio. According to Barberis and Huang (2001), SMR corresponds to the difference between portfolio *A* and portfolio *B*. In other words, it is equal to the difference between the average returns of the companies' portfolio with highest ratio minus the average returns of the companies' portfolio with the lowest ratio.

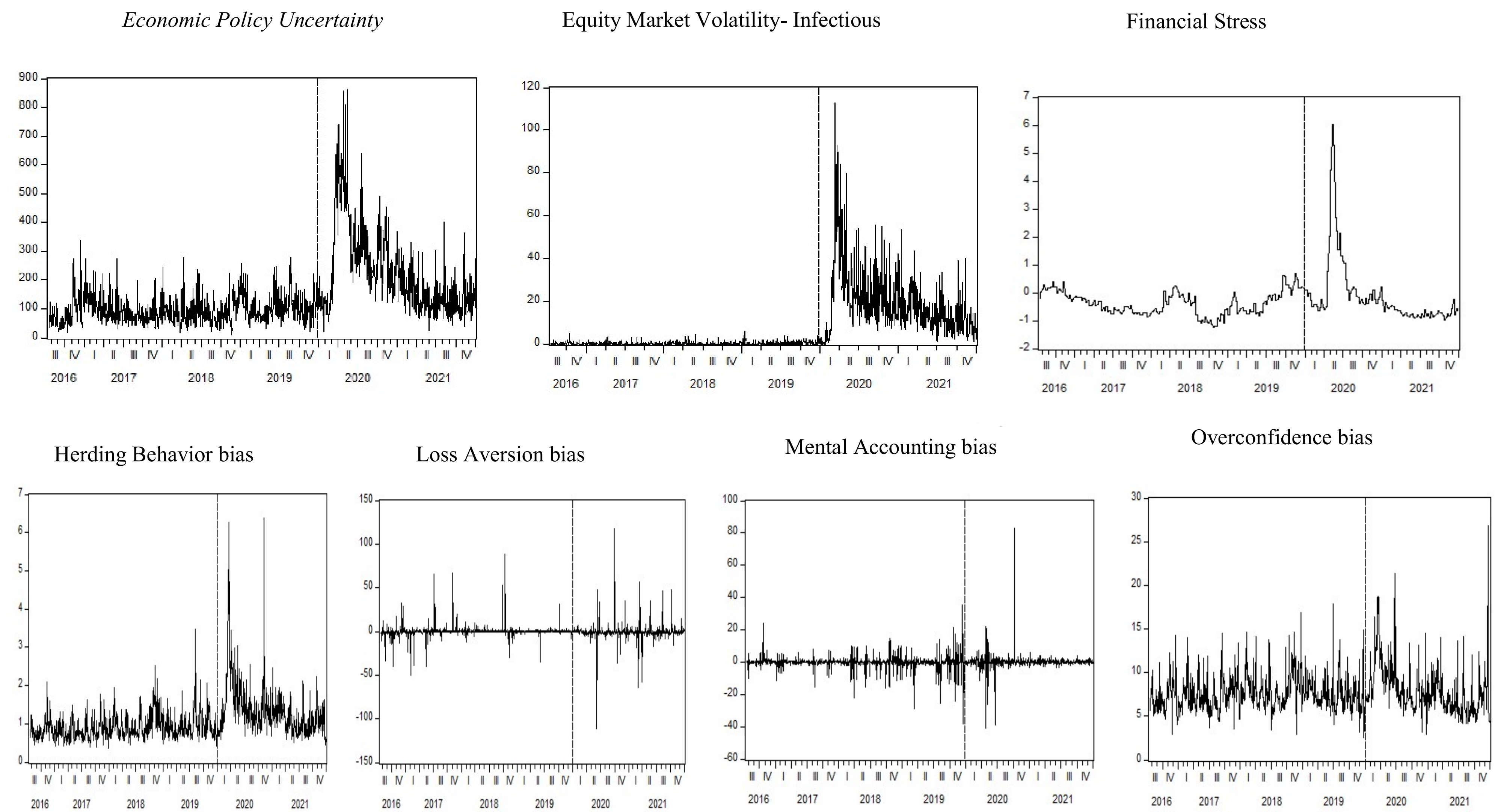
The Overconfidence is calculated (Adel and Mariem, 2013) by using the following formula

$$TR = \frac{n_{it}}{N_{it}} \qquad (6)$$

n_{it} is the number of traded shares of stock *i* (volume traded per days); $\boldsymbol{N_{it}}$ presents the number of exchanges of shares *i* (number of transactions per day). This expression has been used as a measure of the volume and number of transactions (Adel and Mariem, 2013).

Figure 2 illustrates the evolution of the uncertainty factors and behavioral biases. All studied variables have shown both upward and downward trends over the period of the study. There was a sharp decline at the end of 2019 corresponding to the COVID- 19 outbreak.

Figure 2. *Evolution of uncertainty factors and behavioral biases*



3.2. Methodology

This study proceeds in three steps. In the first step, we implement a Johenson co-integration test to examine the long term relationship between uncertainty factors, investor behavioral biases and stock market reaction of listed Fintech companies in the USA. In the next step, we will analyze the bivariate relationship between all the studied variables. To do this, this study relies on the Granger causality tests. In the third step, we rely on a simple ordinary least squares regression to understand the effect of the COVID-19 pandemic on the relationship between uncertainty factors, investor's behavioral biases and stock market reaction of listed Fintech companies in the USA based on the conditional mean functions.

3.2.1. Johansen Cointegration test

In this section, we employed Johansen's test co-integration (1995) to measure the long-term relationship between the variables or the equilibrium through many time series datasets with a linear combination of the studied variables. The test, which is based on the system estimation of multivariate time series, is presented by the following expression based on the VAR of order k:

$$Y_t = a_1 Y_{t-1} + a_2 Y_{t-2} + a_3 Y_{t-3} + \cdots \ldots \ldots .. + a_k Y_{t-k} + bX_t + \varepsilon_t \qquad (7)$$

Y_t represents a p-vector of all the non-stationary variables *I(1)*; X_t is a h-vector of deterministic elements; ε_t is the vector of innovations. This equation can be rewritten as follows:

$$\Delta Y_t = \pi Y_{t-1} \sum_{i=1}^{k-1} \tau_i \Delta Y_{t-i} + bX_t + \varepsilon_t \qquad (8)$$

Where,

$$\pi = \sum_{i=1}^{k} a_i - I \; ; \tau_i = -\sum_{j=i+1}^{k} \alpha_j \qquad (9)$$

Where *I* is the order of integration; π, τ, b are parameters to be estimated; specifically, τ_i and π_i includes information about the short run (long run) adjustments in ΔY_t. If π has reduced rank r < c, there can be exists $p \times r$ matrices for both α and β with rank r; $r = \alpha\beta$ that is stationary.α denoted as resulting parameters of vector error correction model and β is a cointegration vector.

3.2.2. Granger causality test

Granger (1969) implemented causality tests on time series by proposing the use of ordinary least squares method to estimate the following model for two stationary series X_t and Y_t which can be expressed as follow:

$$\Delta Y_t = \sum_{i=1}^{k} \delta_i \Delta Y_{t-i} + \sum_{i=1}^{k} \theta_j \Delta X_{t-j} + \varepsilon_{1t} \qquad (10)$$

$$\Delta X_t = \sum_{i=1}^{k} \alpha_i \Delta X_{t-i} + \sum_{i=1}^{k} \beta_j \Delta Y_{t-j} + \epsilon_{2t} \qquad (11)$$

Where ε_t is the error term. This model is based on the causal relationship between pairwise time series of X and Y. from Equation (10) we can say that the current value of ΔY is related to the historical values of *Y* and the historical values of ΔX. Similarly, Eq. (11) indicates that $\Delta X$is related to the past values of X and that of ΔY. Based on the F test, the null hypothesis of Granger causality test in Eq. (10) is ϑ_j= 0 which means that "Δ*X* does not Granger cause Δ*Y*". Equally, the null hypothesis in Eq. (11) is β_j=0, and states "Δ*X* does not Granger cause Δ*Y*."

3.2.3. Ordinary least squares (OLS) method

Time series analysis must initially indicate that variables are stationary or not. If they are, then, OLS method can be applied to examine the relationship between the selected variables which can be estimated as follow:

$$AR = a_{it} + b_1X_{1it} + b_2X_{2it} + b_3X_{3it} + b_4X_{4it} + b_5X_{5it} + b_6X_{6it} + b_7X_{7it} + e_{it}(12)$$

Where, *AR re*presents Abnormal Returns of the Fintech stock market; X_1 represents the Economic Market Volatility infectious diseases (EMV-ID); X_2 represents Economic Policy uncertainty (EPU) ; X_3 represents the Financial Stress (FS); X_4 represents the Herding behavior(HB); X_5 represents the loss aversion(LA); X_6 represents the Mental accounting(MA); X_7 represents the overconfidence (OC) ; a_{it} represents the independent variables;e_{it} presents theerror term. *i:*from 1 to 48 companies listed in the KFTX index ; *t* represents the sample period.

4. Empirical results

4.1. Descriptive Statistics

Table 1 presents the summary statistics and the unit root test of the main variables for the full period (Panel A), before (Panel B) and during the COVID-19 (Panel C) periods.

In table 1, the results indicate that before the COVID-19 pandemic, the abnormal returns of the Fintech stock market, the behavioral biases and the uncertainty factors had a positive mean value. In fact, the highest mean value is taken by the Economic Policy Uncertainty (95.35130), whereas the lowest is taken by the abnormal returns of the Fintech stock market (0.010550).

Therefore, among all the studied variables, abnormal returns of the Fintech stock market present the lowest risk (0.14). Followed by the Herding behavior (0.316957) then, the Economic Policy Uncertainty presents the highest risk (47.51760). For the behavior biases, the herding behavior presents the lowest risk (0.316957),while Financial Stress (FS) presents the lowest one (11.61%) for uncertainty factors.
Furthermore, findings revealed that during the COVID-19 outbreak, all the variables' mean returns became negative compared to those during the pre-COVID-19 period. Moreover, the standard deviations for all series are higher than their mean and than those during the pre-COVID- period, suggesting a higher level of risk. Furthermore, all the variables have kurtosis values higher than three and the distribution of series is negatively and positively skewed for all the variables, indicating that all the studied variables are not normally distributed. Therefore, the assumption of Gaussian returns is rejected by the Jarque-Bera (1987) test. Besides, the results of the Augmented Dickey Fuller (ADF) test confirm the distributed along with having fat tails including the intensive values of fluctuations during the health crisis of the COVID-19.stationarity of all the variables. At least, we can conclude that all the variables are not normally distributed.

Table 1. *Descriptive statistics summuary for daily variables*

	MEAN	MEDIAN	MAX	MIN	SD	SKEWNESS	KURTOSIS	JACQUE-BERA	ADF
Panel A: Full Period									
AR	-0.011340	-0.009396	1.865000	-1.950000	0.168246	-0.536927	30.37088	42955.73 (0.000)	-14.57076 (0.000)
EPU	140.6516	105.2950	861.1000	10.92000	112.8048	2.432416	10.53069	4601.630 (0.000)	-3.535640 (0.0073)
EMV/ID	6.951798	0.610000	112.9300	0.000000	12.48487	2.887352	14.75751	9823.312 (0.000)	-3.760066 (0.0644)
FS	-0.293317	-0.454000	6.030000	-1.225000	0.795908	4.373918	29.74374	45327.81 (0.000)	-4.771683 (0.0001)
HB	1.062282	0.925235	6.386094	0.368527	0.541553	3.567968	25.68110	32366.51 (0.000)	-6.290245 (0.000)
LA	-0.271353	-0.375521	118.2164	-111.6528	8.334414	1.914557	81.92330	357443.2 (0.000)	-4.26916 (0.0005)
MA	-0.067015	0.017486	82.66055	-40.99291	4.683802	2.599866	91.23746	447287.7 (0.000)	.25.2370 (0.000)
OC	7.632042	7.209067	26.82890	2.526101	2.266446	1.889885	10.43798	3985.186 (0.000)	-5.579674 (0.000)
Panel B: Before COVID-19									
AR	0.010550	-0.002589	0.871317	-1.044263	0.144146	-0.919382	11.06070	2475.054 (0.000)	-30.17323 (0.000)
EPU	95.35130	86.83000	336.7100	10.92000	47.51760	1.312984	5.332950	446.7515 (0.000)	-8.831419 (0.000)
EMV/ID	0.373970	0.000000	5.670000	0.000000	0.655998	3.004404	15.96512	7393.751 (0.000)	25.94738 (0.000)
FS	0.383939	-0.433000	0.669000	-1.225000	0.409481	0.236665	3.389755	21.59607 (0.000)	-2.834862 (0.0583)
HB	0.901599	0.823550	3.472743	0.368527	0.316957	1.858239	10.08512	2317.737 (0.000)	-7.170653 (0.000)
LA	0.013528	-0.176074	88.57815	-49.66207	6.766856	4.060557	70.72504	168464.1 (0.000)	-2.789553 (0.0621)
MA	0.178192	0.008093	35.50192	-38.35141	4.325572	-1.003499	23.83795	15868.23 (0.000)	-21.39789 (0.000)
OC	7.548309	7.239540	17.83911	2.526101	1.909787	1.179211	5.661803	457.9395(0.000)	-9.945360 (0.000)
Panel C: During COVID-19									
AR	-0.012698	-0.015987	1.865000	-1.950000	0.203287	-0.255012	34.04914	20290.67	-8.413850 (0.0000)
EPU	-218.6041	173.4100	861.1000	20.63000	145.4296	1.475526	5.290999	293.6866(0.000)	-3.913850 (0.0731)
EMV/ID	-18.27087	14.92000	112.9300	0.000000	14.86298	2.088614	9.777841	1333.797(0.000)	-3.481310 (0.0923)
FS	-0.137376	-0.504000	6.030000	-0.985800	1.182541	3.268222	14.75633	3807.203(0.000)	-3.82513 (0.0192)
HB	-1.338785	1.174998	6.386094	0.452105	0.710503	3.047570	17.41959	5156.791(0.000)	-4.880716 (0.000)
LA	-0.715016	-0.970794	118.2164	-111.6528	10.49081	0.813477	67.85067	88548.74 (0.000)	-4.54827 (0.0002)
MA	- 0.124296	0.044527	82.66055	-40.99291	5.242319	5.990959	138.5688	389743.4 (0.000)	-26.84246 (0.000)
OC	-7.776131	7.124829	26.82890	2.936289	2.771158	2.071354	10.16614	1441.681(0.000)	-4.21167 (0.0001)

Notes: Critical values of ADF test: 1% level = (-3.44); 5% level= (-2.87); 10%=(-2.5)

4.2. Johansen cointegration test

Although the previous sub section affirmed the stationary of all the variables before and during the covid-19, it is interesting to verify the long-term relationship between these variables by applying Johansen's co-integration test.

In fact, Table 2 provides the trace and Max-Eigen statistics of the multivariate co-integration tests conducted for all the studied variables. Moreover, panel A of the table is related to the full period, panel B concerns the pre-COVID-19 period and panel C concerns the COVID-19 period. Besides, the empirical results in all the sub-periods indicate that there is a long term equilibrium relationship among all the studied variables. Hence, all the time series are co-integrated among themselves at 5% level of significance. This means that there exists an equilibrium relationship between uncertainty factors, the investor behavioral biases and the US Fintech stock market reaction. This result is consistent with what was provided by other studies, such as the one conducted by Aysan et al. (2021), suggesting that there exists a long-run relationship between Altcoins and Bitcoin in both before and during COVID-19 periods.

In fact, these results have a very important implication for the US Fintech stock market investors willing to invest in this stock market. Furthermore, a weak form of co-integration suggests that uncertainty factors, the investor behavioral biases jointly offer potential gains to the diversified portfolio investments in the US Fintech stock market at all-time scales. This integration of international investments could be beneficial to the opportunities of portfolio's diversification of Fintech investors, as well as, the decrease of risk in their activities.

4.3. Granger causality test

Table 3 reports the results of granger the causality test effect between each independent variable and Fintech stock market reaction for variables in the Full, before and during COVID-19 periods.

The results show that Fintech stock market reaction does not causes Equity Market Volatility-Infectious Diseases, Economic Policy Uncertainty and Financial Stress in all sub periods. However, these macroeconomic factors cause the Fintech stock market reaction especially in the full and the COVID-19 periods. This means that COVID-19 pandemic can be the cause of abnormal returns of US Fintech stock market. These findings are consistent with those of Choi (2020) which showed that the economic policy uncertainty leads the volatility of all sectors in USA during COVID-19 pandemic. On the other hand, Liu et al. (2021) demonstrate a non-linear impact of oil price shocks on financial stress.

As for investor's behavioral biases, herding behavior and loss aversion cause the Fintech stock market abnormal reaction in the full and during COVID-19 periods and vice versa. Therefore, this finding corroborates those of Wu et al. (2020), which suggest that the Herding Behavior exists during higher Chinese stock market movement. Indeed, Barberis and Huan (2001) indicated that Loss Aversion can create abnormal returns. However, mental accounting and overconfidence (Fintech stock market reaction) do not cause Fintech stock market reaction (mental accounting and overconfidence) in full and during COVID-19 periods. This result was confirmed by Kuranchie-Pong and Forson (2021) who investigated the relationship between Overconfidence and volatility in Ghana stock market. They indicated that overconfidence bias significantly contribute to weekly volatility during COVID-19 pandemic.

Panel A: Full period							
Hypothesized No. of CE(s)	**Eigen value**	**Trace Statistic**	**Critical Value (5%)**	**Prob.****	**Max-Eigen Statistic**	**Critical Value (5%)**	**Prob.****
None *	0.255840	1006.766	159.5297	0.0001	404.5383	52.36261	0.0001
At most 1 *	0.144391	602.2280	125.6154	0.0001	213.4844	46.23142	0.0000
At most 2 *	0.098578	388.7437	95.75366	0.0001	142.0779	40.07757	0.0001
At most 3 *	0.075520	246.6657	69.81889	0.0000	107.4985	33.87687	0.0000
At most 4 *	0.050213	139.1673	47.85613	0.0000	70.52738	27.58434	0.0000
At most 5 *	0.033153	68.63990	29.79707	0.0000	46.15520	21.13162	0.0000
At most 6 *	0.014477	22.48471	15.49471	0.0038	19.96319	14.26460	0.0056
At most 7	0.001840	2.521515	3.841466	0.1123	2.521515	3.841466	0.0123
Panel B : Before COVID-19							
None *	0.216630	696.2698	159.5297	0.0000	210.9454	52.36261	0.0001
At most 1 *	0.163401	485.3243	125.6154	0.0001	154.1471	46.23142	0.0000
At most 2 *	0.123982	331.1772	95.75366	0.0000	114.3667	40.07757	0.0000
At most 3 *	0.097341	216.8106	69.81889	0.0000	88.48274	33.87687	0.0000
At most 4 *	0.071648	128.3278	47.85613	0.0000	64.23315	27.58434	0.0000
At most 5 *	0.061777	64.09467	29.79707	0.0000	55.09477	21.13162	0.0000
At most 6 *	0.010297	8.999903	15.49471	0.3654	8.943018	14.26460	0.0291
At most 7	6.58E-05	0.056885	3.841466	0.8115	0.056885	3.841466	0.0811
Panel C : During COVID-19							
None *	0.254006	441.8749	159.5297	0.0000	146.5186	52.36261	0.0000
At most 1 *	0.172720	295.3563	125.6154	0.0000	94.80623	46.23142	0.0000
At most 2 *	0.117816	200.5501	95.75366	0.0000	62.67714	40.07757	0.0000
At most 3 *	0.110149	137.8729	69.81889	0.0000	58.35066	33.87687	0.0000
At most 4 *	0.080538	79.52228	47.85613	0.0000	41.98329	27.58434	0.0004
At most 5 *	0.047089	37.53899	29.79707	0.0053	24.11693	21.13162	0.0184
At most 6 *	0.023544	13.42206	15.49471	0.1002	11.91254	14.26460	0.0114
At most 7	0.003014	1.509519	3.841466	0.2192	1.509519	3.841466	0.0219

* denotes rejection of the hypothesis at the 0.05 level, **MacKinnon-Haug-Michelis (1999) p-valu

Table3. *Results of Granger causality test before and during covid 19 periods*

Null hypothesis	Before COVID-19		During COVID-19		Full period	
	F-stat	Prob	F-stat	Prob	F-stat	Prob
EMV-ID does not Granger Cause AR	7.329	0.0185	0.109	0.8960	1.42607	0.0224
AR does not Granger Cause EMV-ID	1.520	0.5218	0.345	0.7079	0.45165	0.1451
EPU does not Granger Cause AR	5.814	0.0183	0.245	0.7821	2.05833	0.0113
AR does not Granger Cause EPU	0.594	0.1552	0.132	0.8760	0.35221	0.1022
FS does not Granger Cause AR	1.333	0.0263	1.029	0.0357	0.80284	0.0441
AR does not Granger Cause FS	3.917	0.1200	0.745	0.1748	1.73284	0,1525
HB does not Granger Cause AR	4.449	0.0118	0.216	0.8054	3.03654	0.0494
AR does not Granger Cause HB	13.73	0.0046	3.381	0.0342	5.8865	0.003
LA does not Granger Cause AR	2.569	0.0767	2.799	0.0610	0.23134	0.0793
AR does not Granger Cause LA	208.97	0.085	226.06	0.0591	4.5311	0.0115
MA does not Granger Cause AR	1.8961	0.1503	1.5488	0.2127	0.53043	0.1755
AR does not Granger Cause MA	135.60	0.0057	48.140	0.0321	29.8509	0,0266
OC does not Granger Cause AR	0.3252	0.7223	0.4145	0.6607	0.1809	0.1202
AR does not Granger Cause OC	4.9522	0.0071	5.5896	0.0038	1.1651	0.0286

4.4. Relationship between uncertainty factors, investor behavioral biases and US Fintech stock market reaction

Table 4 displays the regression results based on the estimation of the long-term relationship of uncertainty factors and the investor behavioral biases with the reaction of the US Fintech stock market. In fact, we showed that EMV-ID has an important positive significant effect, especially, during the COVID-19 pandemic. More precisely, the high spread of corona-virus leads to an over-reaction of the Fintech stock market during the COVID-19 pandemic. However, this finding is contradictory to that of Schell et al. (2020), who stated that the COVID-19 pandemic negatively acts on the abnormal returns of the majority of the stock markets while this phenomenon does not exist in the remaining events (Ebola, Zik…).

Then, the EPU does not affect the Fintech stock market reaction before COVID-19, while, during the COVID-19, the long-term coefficient was negative at the threshold of 1 %, indicating that an increase of the EPU causes an under-reaction of the Fintech stock market. This result differs from those of other studies, which showed that political uncertainty can increase the stock volatility (Brogaard and Detzel, (2015)). According to Chiang (2022), the rise in the economic policy uncertainty in USA causes a decrease in the stock returns of the country and a negative spillover effect on the global market. As concern, financial stress index, its coefficients before and during the COVID-19 pandemic is negatively significant at 5% level. More specifically, the Fintech stock market under-reacts the common signal of financial stress in a long-term horizon. Therefore, these results can be explained by the increased consequences of financial crisis, more precisely during the 2020 health crisis. For example, Jana et al. (2022) affirmed that US financial stress has caused maximum spillovers to the emerging markets during COVID-19 in a long term horizon. On the other hand financial stress events cause extreme values of uncertainty or an expected loss in financial markets; as these shocks are transmitted throughout the economic system, which disrupts the financial system. Therefore, this can result in uncertainty about the fundamental value of financial assets or the investor's behavior, which increased the asymmetric information; and showed a less willingness to hold risky or illiquid assets (Hakkio and Keeton 2009).

Moreover, we show that herding behavior has a significant positive effect on the reaction of the US Fintech market. Thirikwa and Olweny (2015) showed that herding behavior was more pronounced when market returns, transaction volume and volatility were high. In addition, our findings are consistent with Wu et al. (2020) which indicated that herding behavior in the Chinese stock market is more apparent for upside market movement.

Therefore, we can clearly see that before the COVID-19 pandemic, the results indicated that loss aversion does not affect the reaction of the Fintech stock market. For their part, Easley and Yang (2015) indicated that while loss averse investors and arbitrators differ only in the way they derive the loss aversion utility, loss averse investors disappear and have no significant effect in the long run. Moreover, we found that during the COVID-19 pandemic, the increase of the investor's loss aversion led to an under-reaction of the US Fintech stock market reaction. This result was confirmed by Barberis and al. (2001), who indicated that loss aversion behavior could lead to stock prices abnormal returns. These results also showed that investors do not care about losses or gains in utility in their investment decisions in the American Fintech stock market in the normal period (before the COVID-19) but in the crisis period (during COVID-19), investors become more sensitive to losses than to gains (they become more pessimistic).

However, before the outbreak of the COVID-19 pandemic, mental accounting acted positively and significantly on the US Fintech stock market reaction while during the pandemic; there is a negative significant effect between these two variables in the long run.

Finally, overconfidence bias has a significant positive relationship with the US Fintech stock market reaction before the COVID-19 pandemic. Accordingly, these results are consistent with those of Metwally and Darwish (2015), who found that overconfidence, has a positive and statistically significant effect on the stock market reaction. Further, Mushinada and Veluri (2018) showed that the overconfidence bias based on the trading- volume's component is positively correlated with the market volatility. This bias reflects the investor's optimism in the face of the emergence of the Fintech. In fact, investors are still overconfident and likely ready to trade more aggressively resulting in an over-reaction of the Fintech stock market in the long run. Investors should therefore carefully assess the effect of the overconfidence variable when making investment decisions to check whether stock prices have moved away from fundamental values. However, during the COVID-19 period, overconfident investors lead to under-reaction of the American Fintech stocks. This result can be explained by the drastic drop in the asset quality caused by economic hardship during the Covid-19 pandemic, which is likely to decrease confidence in the financial markets.

Table 4.*Impact of COVID-19 on the relationship between uncertainty factors, investor behavioral*

Variables	Coifficients	Std-error	Probability	T-statistic
Full Period				
EMV-ID	0.0042	0.002190	-1.915177	0.1556
EPU	0.0011	0.000195	-5.394346	0.0000***
FS	-0.0699	0.030855	-2.267622	0.0234**
HB	0.1421	0.048719	-2.916229	0.0036***
LA	-0.0060	0.000149	39.70950	0.0000***
MA	-0.0015	7.08E-05	-21.16424	0.0000***
OC	0.0106	0.006217	1.705448	0.01882
R-squared	0.6739		**Mean dependent var**	0.03298
Adjusted R-squared	0.6731		**S,D, dependent var**	0.96186
S,E, of regression	0.5499		**Sum squared resid**	856.0966
Long-run variance	0.8519			
Panel B : Before COVID-19				
EMV-ID	0.0147	0.0031	4.7392	0.1825
EPU	-0.0017	0.0003	-5.7342	0.1181
FS	-0.0094	0.0369	-0.2548	**0.0127****
HB	0.0345	0.0487	-0.7076	**0.0047*****
LA	-0.0043	0.0001	24.6191	0.1861
MA	0.0006	0.0004	4.7082	**0.0239****
OC	0.0132	0.0049	2.7242	**0.0065*****
R-squared	0.434915		**Mean dependent var**	0.027690
Adjusted R-squared	0.433337		**S,D, dependent var**	0.602247
S,E, of regression	0.453354		**Sum squared resid**	515.2625
Long-run variance	0.416371			
Panel C : During COVID-19				
EMV-ID	0.0314	0.0180	-1.7373	**0.0000*****
EPU	-0.0065	0.0002	3.1247	**0.0000*****
FS	-0.0982	0.0326	-3.0045	**0.0399****
HB	0.0864	0.0665	1.2994	**0.0000*****

LA	-0.0079	0.0002	47.3768	**0.0194****
MA	-0.0012	0.0775	-18.8987	**0.0000*****
OC	-0.0312	0.0137	-2.2877	**0.01228****
R-squared	0.892388		**Mean dependent var**	0.075075
Adjusted R-squared	0.889996		**S,D, dependent var**	2.306582
S,E, of regression	0.765019		**Sum squared resid**	184.3551
Long-run variance	0.631132			

***, **, * represent the significance threshold of 1, 5 and 10% respectively

5. Conclusion

This paper aims to investigate the impact of uncertainty factors and investor behavioral biases on the stock reaction of US Fintech stock market before and during COVID-19 pandemic. Our data span the period from July 20, 2016 to December 31, 2021.
In the first step, we implement a Johansen cointegration test to examine the long-run relationship between uncertainty factors, investor behavioral biases and stock market reaction of listed Fintech companies in USA. In the second step, we analyze the bivariate relationship between all studied variables using Granger causality tests. In the third step, we employa simple ordinary least square regression to understand the effect of COVID-19 pandemic on the relationship between uncertainty factors, investor behavioral biases and stock market reaction of listed Fintech companies in USA.
In fact, Johansen cointegration test results indicate that there is long-run equilibrium relationship among all studied variables before and during COVID-19 pandemic. Hence, all times series are cointegrating among themselves at 5% level of significance. Furthermore, the granger causality test findings indicate that the level of integration and causality relations among uncertainty factors and investor behavioral biases with the US Fintech stock market reaction tends to change over time, mainly during COVID-19 crisis.
In summary, the empirical findings in this study shed new lights that COVID-19 will have a crucial effect on abnormal Returns in Fintech stock market due to the rapid spread of COVID-19 and bad news related to EMV-ID and EPU results. Additionally, during COVID-19, much of daily life moved online Fintech have seen increased fraud and cyber-security risk with the significant effect of financial stress, which result higher abnormal returns. As well as, the instability of prices makes investors irrational when they use mental bias. More importantly, overconfidence bias makes investors overestimate their abilities, which affects the stock markets risk.
these empirical results suffer from prominent implications to protect the US Fintech stock market from shocks during crises. Firstly, the increase of the economic policy uncertainty factors during the Covid-19 pandemic requires the implementation of proactive policies to reduce bad news of these factors, which play a very important role in the under-reaction or over-reaction of the Fintech stock market. Secondly, the multitude of uncertainty factors, especially in the period of the Covid-19 pandemic, can affect the behavior biases of investors who can make decisions mistakes and then abnormal returns of Fintechs stock markets. Moreover, this work may be useful to policy makers and investors in the Fintech stock markets as it considers behavioral factors in their investment decisions. Furthermore, based on technology trading and predetermined rules, investors can automatically make trading decisions in order to reduce mistakes while, the investor’s psycho-emotional risks associated with capital market trading activities remains high, mainly in the period of crisis. For this reason, governments and private planners who create ex ante rules, like disclosure, reporting, advertising and regulations, must avoid actions that intensify the investor’s biases.

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