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RESEARCH PAPER

Stock Markets and Exchange Rates Throughout the COVID-19 Pandemic: Other Evidence for Italy and China Case

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Abstract
This paper examines the impact of changes in COVID-19 cases/deaths on the stock market and exchange rate using daily data covering the period between 31 December 2019 and 12 March 2020, in Italy and China. Founded on the Markov Regime Switching model, we identified two stress regimes: normal stress regime and high-stress regime. The threshold VAR Model is used to differentiate the exchange rate and stock market price dynamics between normal stress regimes and high-stress regimes. We found that of COVID-19 pandemic has no/weakly impact on Chinese and Italian national currencies but can negatively influence stock market prices. The contribution of this framework is the setting of an estimated threshold value of the number of deaths/cases of COVID-19 above what we consider a high-stress period. These findings are very important for policymakers to predict sanitary pandemic effects such as COVID-19 on the global markets and help in policies' perception of fighting against any sanitary pandemic.
Keywords: Markov Switching, Sanitary Disease, Stock Market Prices, Stress Period, TVAR Model.
JEL Classification: C1, C3, G1, G150.

1. Introduction
The COVID-19 pandemic started in China then it spread in Europe, and specifically in Italy. Italy now is considered the first European epicenter followed by Spain. It has been hit hard so far with serious Coronavirus outbreaks. In 2020

the country had more than 746,146 deaths considered as the highest level since the Second World War[1].

Given the global impact of this pandemic, there have been considerable numbers of papers that discussed the cost of COVID-19 both in terms of social costs or financial/economic costs. For instance, the study of Goodell (2020) is considered the pioneering work regarding the economic/social impacts of natural disasters. The author used a comprehensive literature review to show that Coronavirus is causing unprecedented global damage and may have a serious impact on stock markets. Chen and Yeh (2021), studied industrial reactions to COVID-19 and the financial crisis and found that quantitative easing on stock performance has a more significant effect on industries that are more affected by coronavirus. Chatterjee et al. (2021) developed a new financial stress index for the United Kingdom and found no relationship between financial shocks contributing to the COVID-19 crisis.

Studying the Relationship between Exchange Rate and Stock Price can put more emphasis on the effects of coronavirus on financial sector conditions in many countries and thus improve the decisions required to be undertaken by policymakers to support economic/financial development. For instance, Devpura (2021), using a predictive regression model, found no relationship between the Euro/USD exchange rate and oil price during the COVID-19 period. Szczygielski et al. (2021) found that COVID-19 has a negative impact on regions and that Asian markets are stronger compared to others. Using quantitative and qualitative investigations to analyze the cross-correlations between Chinese A-share and B-share markets, Wang et al. (2010) found that the cross-correlations were strong in the short term and weak in the long term. In a study based on bivariate regressions, Ali et al. (2020) investigated the fluctuations in financial markets when the COVID-19 epicenter moved from China to the rest of the world. Baker et al. (2020) showed that the impacts of the COVID-19 pandemic on the fluctuations in the U.S. stock market were considered without historical precedent. On the other hand, Ashraf (2020) examined the impact of COVID-19 on stock markets and found that the number of confirmed deaths does not affect stock markets. However, the decrease in returns was more obvious for the initial days and then between 40 to 60 days of the outbreak. Rahman et al. (2021) examined the effects of COVID-19

1. Italian National Statistics Agency Report

on the Australian stock market and found a negative reaction. Using an empirical analysis based on non-parametric tests, Qing et al. (2020) showed that, in many countries such as Italy, the People's Republic of China, Spain, and France, the impact of the COVID-19 pandemic on stock markets is negative.

Our study complements the ongoing literature about the economic/financial impacts of the coronavirus pandemic. We rely on the works of Hubrich and Tetlow (2015), Liu et al. (2019), and Barnichon et al. (2020), who show that financial shocks can be very different when switching from a normal period to a stress period. We used a monthly Bayesian TVAR model to pick out and emphasize economic dynamics during two regimes: normal stress regime vs. high-stress regime for Italy and China. The contribution of TVARs is that the period of a high-stress regime is explicitly defined where the number of COVID-19 cases/ deaths is above an estimated threshold value for each country.

The remainder of the paper is organized as follows. Section 2 presents the econometric methodology. Data and empirical analysis are reported in section 3. Finally, we conclude and give some implications in section 4.

2. Econometric Methodology

2.1 Markov Regime Switching Model

In this paper, we follow a statistical approach based on a Markov regime-switching model to identify the stress period. For a more detailed analysis, we use the following equations:

$$Regime\ 0: \quad Y_t = \emptyset_{0,0} + \emptyset_{1,0} Y_{t-1} + \cdots + \emptyset_{P,0} Y_{t-P} + \varepsilon_{t,0} \quad \text{if} \quad S_t = 0 \tag{1}$$

$$Regime\ 1: \quad Y_t = \emptyset_{0,1} + \emptyset_{1,1} Y_{t-1} + \cdots + \emptyset_{P,1} Y_{t-P} + \varepsilon_{t,1} \quad \text{if} \quad S_t = 1 \tag{2}$$

where $\varepsilon_{t,j} \sim N(0, \sigma_j^2)$. S_t , the random variable depending on the prevailing regime[1]. If there are two regimes, take on the values 0 and 1.

The Markov regime switching model assumes the existence of two regimes ("Normal" and "High"), where the regime 0 (*Normal Stress Regime*) defines the lower values of conditional variance[2] h_{it} and the regime 1 (*High Stress Regime*) their higher values. This model can be used to take into account endogenous

[1]. Following Hamilton (1989), assume that S_t is a first-order Markov-process, which means that the current regime (S_t) depends only on the regime in the preceding period (S_{t-1}).

[2]. The conditional variance are obtained from estimating the univariate AR(0) – EGARCH (1,1) model during the entire sample period.

structural breaks and thus allows the data to determine the beginning and end of the stress period.

2.2 Threshold VAR Model

2.2.1 Identification of ThresholdVAR Model

The threshold VAR methodology applied in this paper follows Tsay (1998) and Balke (2000). The model is given by the following in Equation (3):

$$Y_t = A^1 Y_t + B^1[L]Y_{t-1} + (A^2 Y_t + B^2(L)Y_{t-1})I[s_{t-d} > \gamma] + u_t \quad (3)$$

In this model, Y_t is a vector of endogenous variables; I,is an indicator function that equals one if the threshold variable $s_t$at lag order d (the delay parameter) is greater than the threshold γ and zero otherwise. The delay parameter d implies that if the threshold variable s_{t-d}crosses the threshold value of γ at time $t - d$; the dynamics change at time.

B^1 and B^2 are the polynomial lag matrices and $A^1 Y_t$ and $A^2 Y_t$ represent the contemporaneous terms. It is reasonable to assume that contemporaneous terms might change across regimes. It also the matrices $A^1$and A^2have a recursive structure.

2.2.2 Hypothesis Testing and Estimation of ThresholdVAR Model

If the threshold $\gamma$was known beforehand, the conventional F-test for the null hypothesis $A^2 = B^2(L) = 0$ could give reliable results. However, in our case, the threshold value is not known a priori, and the testing procedure involves non-standard inference because γ is not identified under the null hypothesis of no threshold[1]. To take into account this nuisance parameter problem, two separate test procedures are conducted. The first one is the arranged regression test of Tsay (1998), which transforms the threshold model into a change point problem. The data get organized in ascending order of the threshold variables_{t-d}. Under the null of linearity, the residuals of the rearranged regression would be correlated with the regressors of the system. Due to the rearrangement, an F-test for the parameter matrix of the system, in which the predictive residuals are regressed on the vector of target variablesY_t, would asymptotically follow a χ^2 distribution. The second test procedure is suggested by Andrews and Ploberger (1994) and Balke (2000). Instead of transforming the system into a change point problem, which would obtain standard inference, Andrews and Ploberger (1994) suggest using three

[1]. see Afonso et al. (2018).

separate test statistics, one with the maximum value of the Wald-statistic (sup-Wald), one with the average of the Wald-statistic (avg-Wald) and one with the sum of the exponential Wald statistic (exp-Wald), in which the critical values of these test statistics are non-standard, the bootstrap technique proposed by Hansen (1996) is applied to simulate the unknown asymptotic distributions.

In the end, the VAR lag L, the threshold γ and the threshold lag d are estimated via the Akaike information criterion. For various combinations of L and d, the corresponding threshold variable s_{t-d} is ordered and the model is estimated via the maximum likelihood method for the respectively defined subsamples and for each possible realization of s_{t-d}. To have a minimum set of data in each regime and to avoid overfitting, the top and bottom 15% of the realizations plus a number of parameters for an individual equation of the model are left out as potential thresholds[1]. The optimal combination of the lag length $\hat{L}$, the threshold lag $\hat{d}$ and the threshold value $\hat{\gamma}$ is selected by the values of the set $\{L, d, \gamma\}$, which minimizes the Akaike information criterion.

3. Empirical Results

3.1 Data and Preliminary Analyses

For our study, we have used daily data covering the period between 31 December 2019 and 12 March 2020. Daily data on FTSE/USD[2] and CNY/USD are obtained from the Federal Reserve Economic Data. Daily data on the FTSE/USD and SSE/USD are obtained from the yahoo finance. Daily data on the COVID-19 deaths and cases are obtained from the web page of Alessia Paccagnini[3]. We use the logarithm for all data series. The table below presents the descriptive statistics for this database.

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[1]. This choice of 15% trimming is a common one in the T-VAR literature. See, for instance, Hansen (1999; 2000), Tsay (1998), Calza and Sousa (2006), Hubrich and Teräsvirta (2013), and Evgenidis and Tsagkanos (2017).

[2]. Description of the different stock market are available in Appendix 1

[3]. https://sites.google.com/site/alessiapaccagnini/covid19?authuser

Table 1. Descriptive Statistics

Variables	Mean	Max	Min	Std. Deviation	Skewness	Kurtosis	Jarque-Bera
				Italy			
EURO/USD	0.0999	0.1308	0.0758	0.0131	-0.1069	2.5251	0.8251*
FTSE/USD	10.0547	10.1455	9.6087	0.0879	-2.8223	12.4385	367.8871*
Cases	1.5866	7.7463	0.0000	2.6671	1.2203	2.7382	18.3277*
Deaths	0.6996	5.2781	0.0000	1.4532	1.9625	5.5144	66.0908*
				China			
CNY/USD	1.9392	1.9499	1.9255	0.0066	-0.2222	2.2651	2.2434*
SSE/USD	8.0040	8.0441	7.9181	0.0281	-0.7448	3.1391	6.8082*
Cases	4.8787	9.6251	0.0000	2.9271	-0.5616	2.0087	6.8258*
Deaths	2.658232	5.5373	0.0000	1.9046	-0.4494	1.6080	8.3508*

Source: Research finding.

Note: The superscript *, ** and *** denotes the 1%, 5%, and 10% levels of significance.

According to summary statistics given in Table 1, the EURO/USD and CNY/USD exhibit low degrees of volatility, as reflected in their standard deviations. The standard deviations are between 0.001 and 0.02. FTSE/USD is the largest one. All returns series, have small negative skewness except cases and deaths in Italy. The negative skewness implies that large negative changes occur more often than positive changes. The kurtosis statistics are positive for all returns series, indicating that the tails have more observations than the Gussian distribution. This is also confirmed by the large Jarque-Bera statistics, which reject the null hypothesis of normal distribution for all series.

Table 2. Unit Root Tests

	ADF Test			KPSS Test	
Variables	**Constant**	**Constant & Trend**	**Pays**	**Constant**	**Constant & Trend**
			Italy		
EURO/USD	-7.3655*	-7.7640*		0.4050*	0.1367*
FTSE/USD	-16.9192*	-17.3045*		0.3519*	0.0616*
Cases	-9.4162*	-9.8842*		0.4609*	0.0634*
Deaths	-1.3582	-10.1398*		0.7096*	0.1843*
			China		
CNY/USD	-8.2253*	-8.2274*		0.1254*	0.0764*
SSE/USD	-9.1561*	-9.0874*		0.0527*	0.0547*
Cases	-13.9795*	-14.3609*		0.2536*	0.0825*
Deaths	-9.6222*	-10.0662*		0.1314*	0.1259*
Test Critical Values				0.7390	
1%*	-3.5256	-4.0925		0.4630	0.2160
5% **	-2.9029	-3.4743		,	0.1460
10% ***	-2.5889	-3.1644		0.3470	0.1190

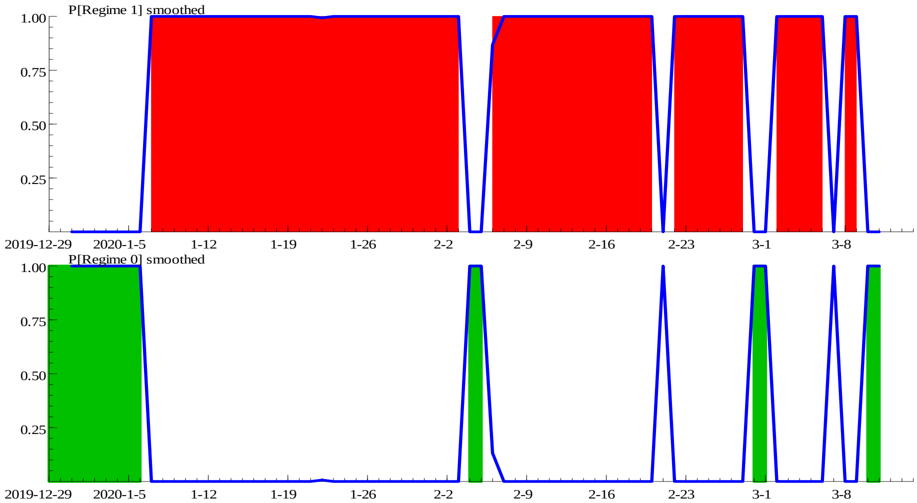
Source: Research finding.

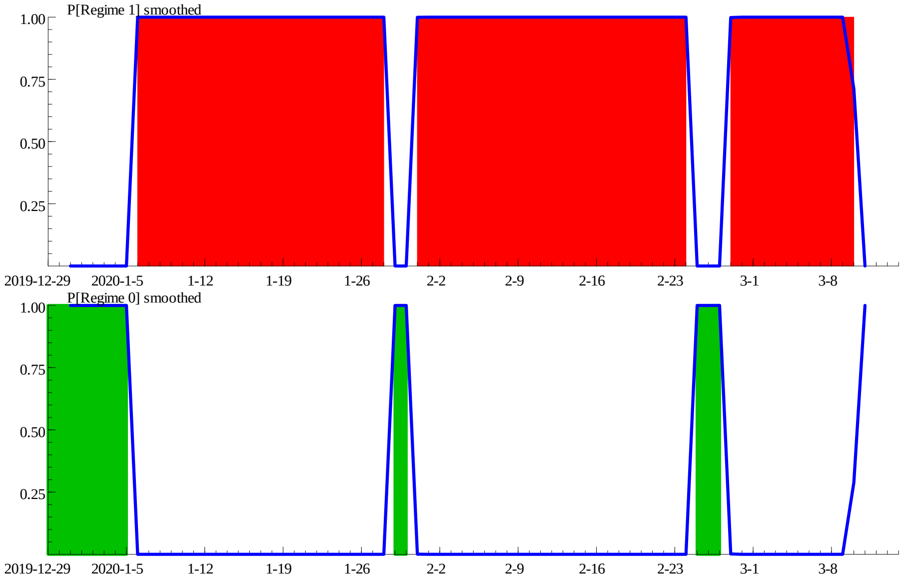
Note: The superscript *, ** and *** denotes the 1%, 5% and 10% level of significance.

We check the presence or absence of unit roots for the different components of this database from the unit roots tests in Table 2. According to the ADF test, deaths in Italy are stationary at %1 in a model with a constant and trend and non-stationary in a model with a constant. All other variables are stationary at the %1 significance in a model with constant and with constant and trend. Hence, we continue to cross-check the stationary of all variables with the KPSS test. The KPSS test indicates that all variables are stationary at the %1 significance.

3.2 Specification and Analysis of Periods of Stress

EURO **FTSE**


P[Regime 1] smoothed
1.00
0.75
0.50
0.25
2019-12-29 2020-1-5 1-12 1-19 1-26 2-2 2-9 2-16 2-23 3-1 3-8
P[Regime 0] smoothed
1.00
0.75
0.50
0.25
2019-12-29 2020-1-5 1-12 1-19 1-26 2-2 2-9 2-16 2-23 3-1 3-8


P[Regime 1] smoothed
1.00
0.75
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0.25
2019-12-29 2020-1-5 1-12 1-19 1-26 2-2 2-9 2-16 2-23 3-1 3-8
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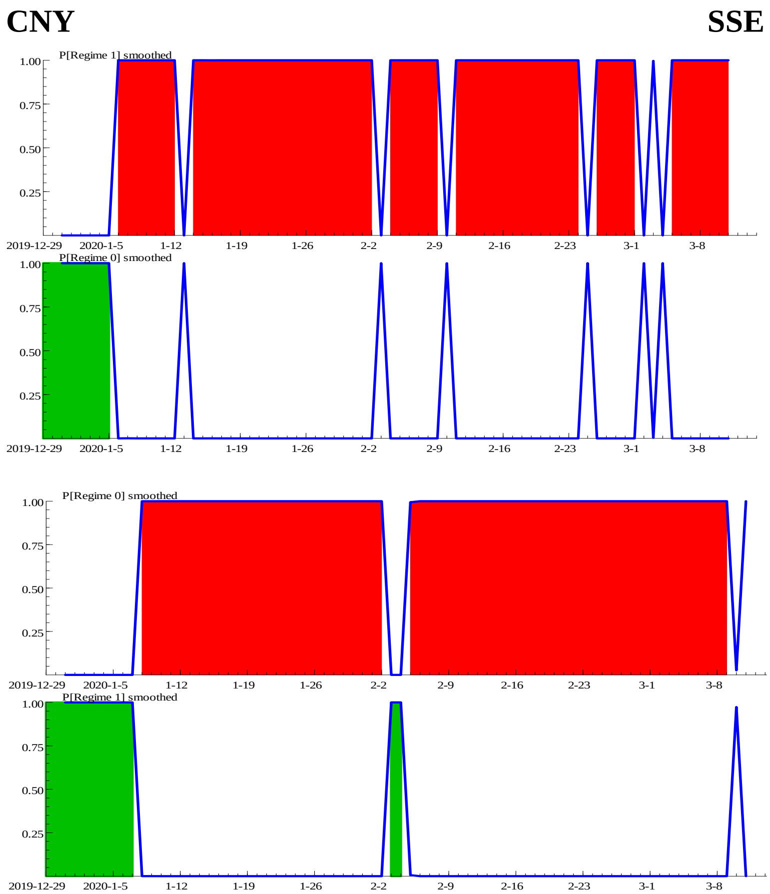
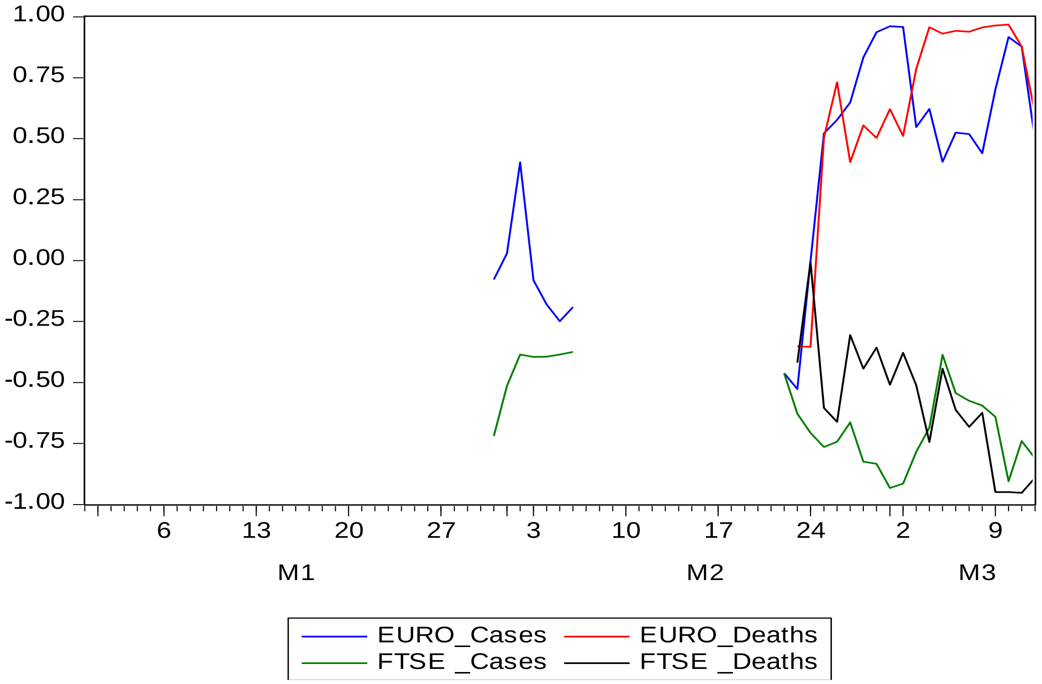


Figure 1. Regime Classification with Conditional Variance
Source: Research finding.

The smoothed regime probabilities of h_{it} depicted in the Figures above reveal the normal stress regime/high-stress Regime for each EURO/USD, FTSE/USD, CNY/USD, and SSE/USD. Regime1, in red, denotes periods of high-stress regime. The blue columns indicate the smoothed regime probabilities, while the green spaces are the regimes 0 of the normal stress regime according to the Markov regime-switching model.



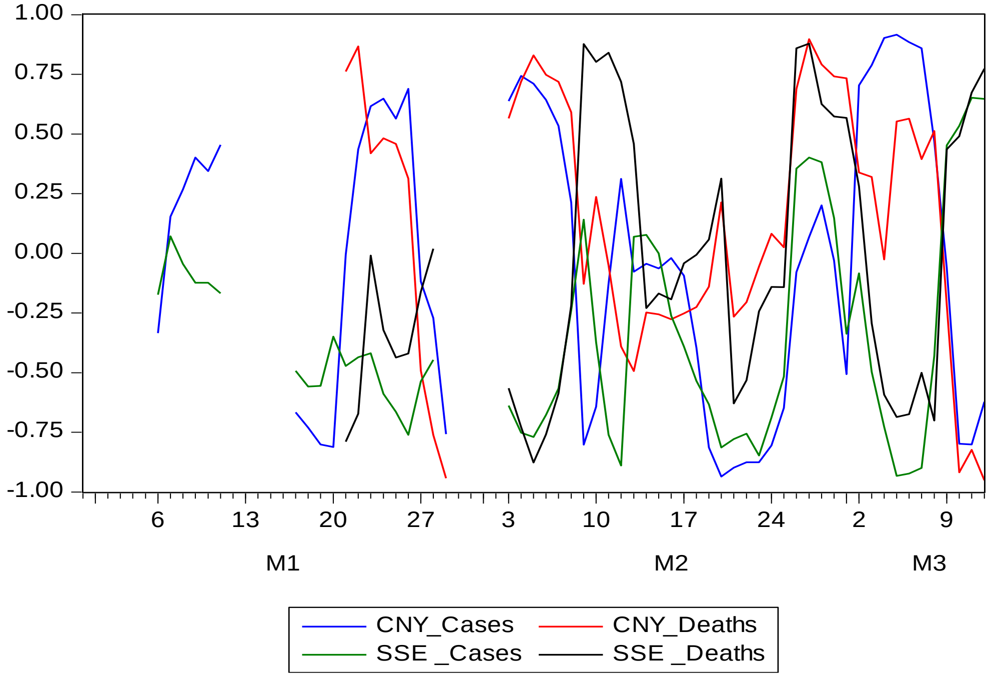


Figure 2. Rolling Correlation One Week

Source: Research finding.

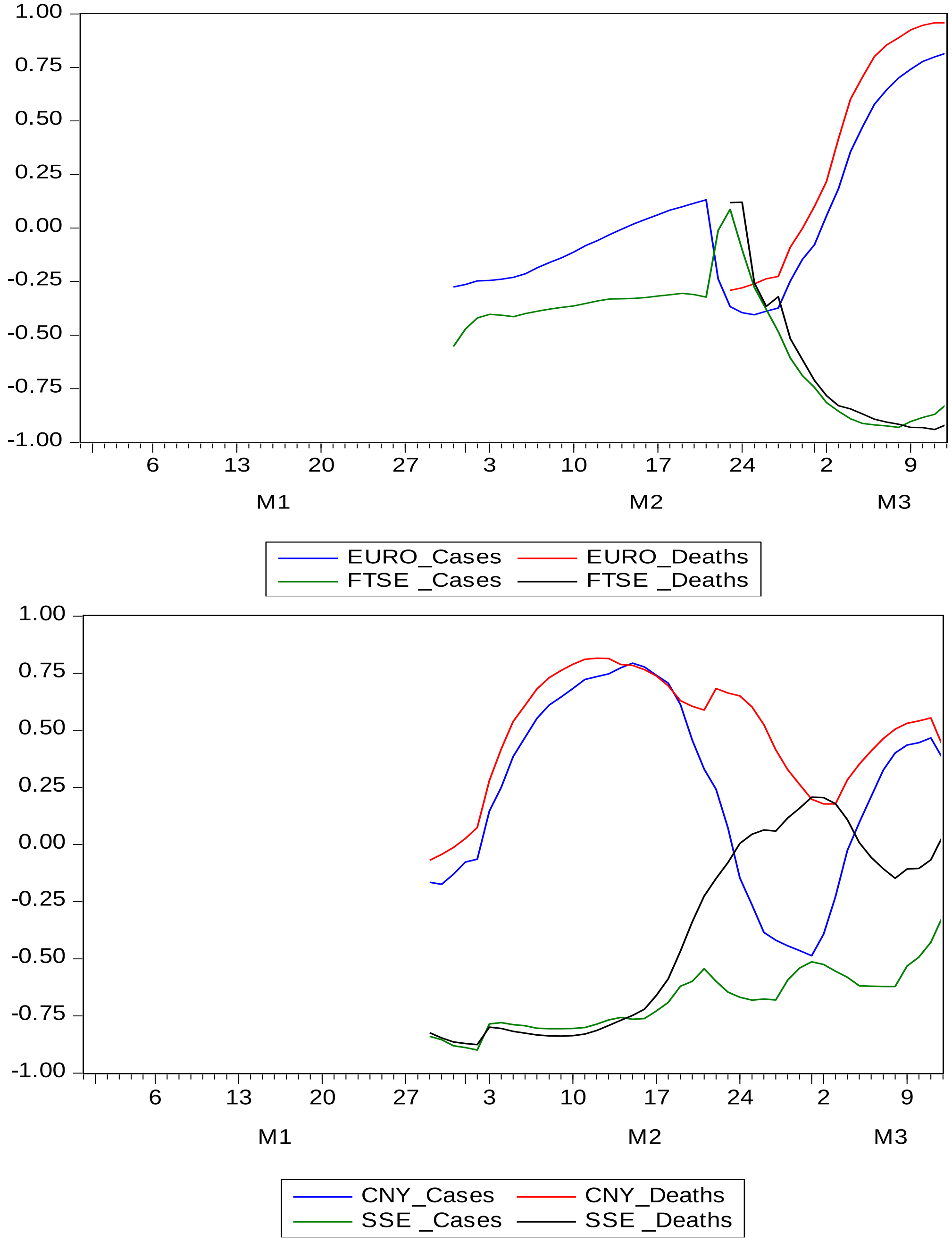
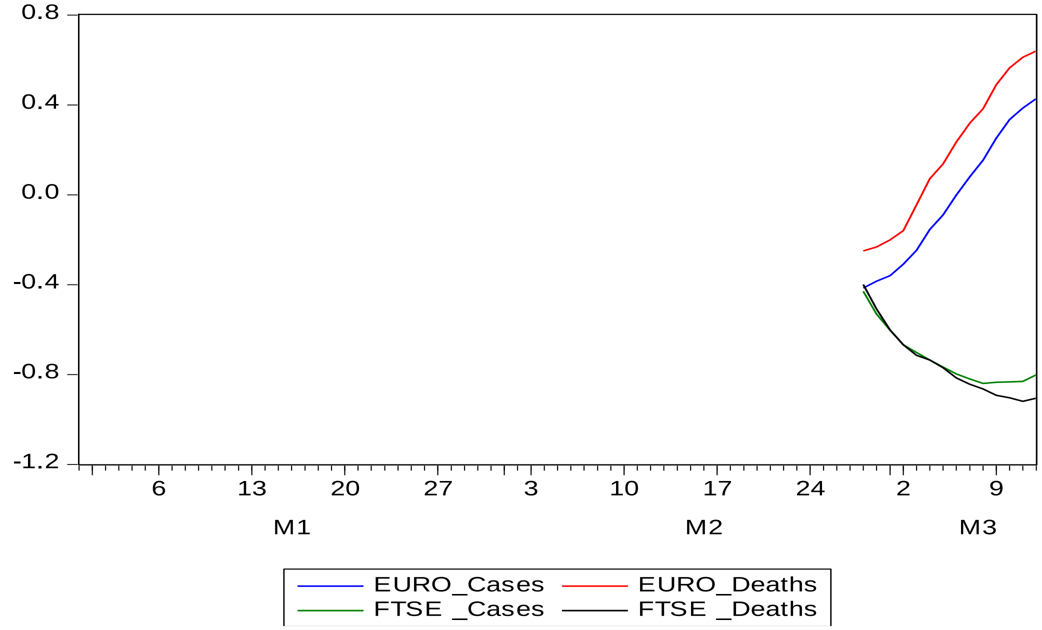


Figure 3. Rolling Correlation One Month

Source: Research finding.



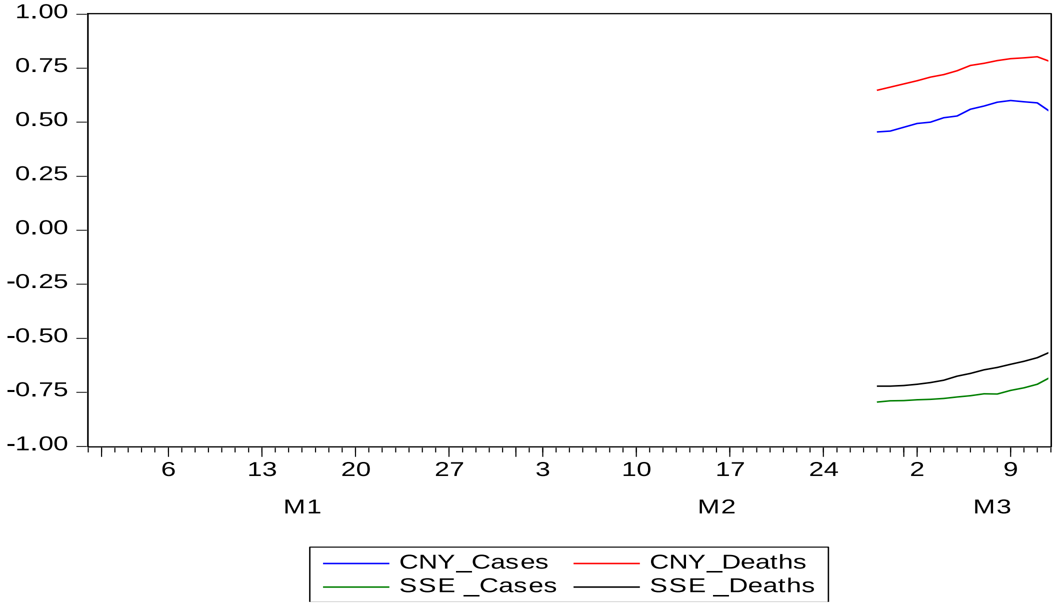


Figure 4. Rolling Correlation Two Months
Source: Research finding.

In the Figures above, we plot the rolling correlations between each pair of EURO/USD_Cases, EURO/USD_Deaths, FTSE/USD_Cases, and FTSE/USD_Deaths with periods of one week, one month, and two months, respectively. In most cases, results show that the correlation between prices became higher and higher over time. Interestingly, we find more fluctuations of the rolling correlations in downward directions between each pair of FTSE/USD_Cases and FTSE/USD_Deaths, particularly after two months. Moreover, graphs reveal several breaks. These findings may be explained by the quarantine periods (periods of economic isolation) when the stock market falls.

3.3 Non-linearity Test and Estimation of the TVAR Model

Tables 3 and 4 display the estimation results of the threshold value, the threshold lag, and the VAR lag length, as well as the described nonlinearity tests. The estimated threshold is $\hat{\gamma}$ with a corresponding threshold lag of $\hat{d}$ and a VAR lag length of $\hat{L}$. The left column shows the results of the threshold, threshold lag, and VAR lag estimation, which are jointly selected via AIC for all possible values of the threshold variable (excluding 15% trimming). The second column from the left displays the results for the arranged regression test of Tsay (1998), where C(1) is the test statistic calculated for one threshold lag. The three rightmost columns show the Sup-Wald, Avg-Wald, and Exp-Wald test statistics of Andrews and Ploberger (1994) and Balke (2000). The nonlinearity test of Tsay (1998) rejects the null hypothesis of linearity at the 5% significance level. In line with the Tsay (1998) test, the simulation-based tests of Andrews and Ploberger (1994) and Balke (2000) indicate that the null hypothesis of no threshold nonlinearity is rejected at the 1% significance for all three test statistics. Therefore, the nonlinearity tests provide strong evidence in favor of a threshold model.

Table 3. Threshold Nonlinearity Test, Threshold, Threshold Lag and VAR Lag Estimation

Italy					
		Tsay (1998)	Andrews and Ploberger (1994)/ Balke (2000)		
			Sup-Wald	Avg-Wald	Exp-Wald
EURO/USD_Cases	**Threshold** $\hat{\gamma}$ =3.3830=29.46 **ThresholdLag** $\hat{d} = 1$ **VAR Lag** $\hat{L} = 1$	C(1) 5.033*	19.60 *	5.71*	6.98*
EURO/USD_Deaths	**Threshold** $\hat{\gamma}$ = 0.3465=1.41 **ThresholdLag** $\hat{d} = 1$ **VAR Lag** $\hat{L} = 1$	4.819*	19.60*	5.17*	6.89*
FTSE/USD_Cases	**Threshold** $\hat{\gamma}$ = 4.4446=85.165 **ThresholdLag** $\hat{d} = 1$ **VAR Lag** $\hat{L} = 1$	8.201*	6.51*	3.14*	1.87*
FTSE/USD_Deaths	**Threshold** $\hat{\gamma}$ = 0.8047=2.236 **ThresholdLag** $\hat{d} = 1$ **VAR Lag** $\hat{L} = 1$	5.215*	6.51*	3.20*	1.90*

Source: Research finding.

Note: The superscript *, ** and *** denotes the 1%, 5%, and 10% level of significance. Values are in the natural log, we must apply an exponential function to find the real value: for example $\hat{\gamma}$ =3.3830 the real value = e($\widehat{\gamma}$ =3.3830) =29.46.

Table 4. Threshold Nonlinearity Test, Threshold, Threshold Lag and VAR Lag Estimation

China					
		Tsay (1998)	Andrews and Ploberger (1994)/ Balke (2000)		
		C(1)	Sup-Wald	Avg-Wald	Exp-Wald
CNY/USD_Cases	Threshold $\hat{\gamma}$ = 7.7217=2256.792 Threshold Lag $\hat{d} = 1$ VAR Lag $\hat{L} = 1$	6.629*	40.46*	8.01*	17.38*
CNY/USD_Deaths	Threshold $\hat{\gamma}$ = 3.8176=45.494 ThresholdLag $\hat{d} = 1$ VAR Lag $\hat{L} = 1$	5.541*	23.15*	5.65*	8.45*
SSE/USD_Cases	Threshold $\hat{\gamma}$ = 7.8200=2489.905 ThresholdLag $\hat{d} = 1$ VAR Lag $\hat{L} = 1$	7.228*	16.98*	4.14*	4.85*
SSE/USD_Deaths	Threshold $\hat{\gamma}$ = 3.659=38.822 ThresholdLag $\hat{d} = 1$ VAR Lag $\hat{L} = 1$	4.592*	10.43*	7.38*	4.06*

Source: Research finding.
Note: The superscript *, ** and *** denotes the 1%, 5%, and 10% level of significance. Values are in the natural log, we must apply an exponential function to find the real value: for example $\hat{\gamma}$ =7.7217 the real value = e($\widehat{\gamma}$ =7.7217) =2256.792

Moreover, the TVAR model enables us to determine a threshold value in terms of number of COVID-19 cases and deaths. The estimation reveals interesting findings. For Italy (Table 3), results show that beyond 30 COVID-19 cases, the EURO/USD exchange rate goes from the normal stress period to the high-stress period. In addition, it suffices 2 COVID-19 deaths to switch to the period of high stress. For the pair, FTSE/USD several 85 COVID cases can make it go from the normal period to the high-stress period. In addition, when the number of deaths exceeds 2, it will change to the high-stress period. For China (Table 4), the threshold values are much higher. The pair CNY/USD switches to the period of high stress in the presence of more than 2256 COVID cases and 45 deaths. Likewise, in the presence of 2490 COVID cases and more than 38 COVID deaths, the SSE/USD exchange rate passes from the normal stress regime to the high-stress regime. These findings are very important for policymakers to predict COVID-19 pandemic effects and help in policy perception of fighting against COVID-19. When the number of COVID-19 cases and deaths reach the estimated threshold values, Italy and China can avoid switching to the high-stress period and maybe the decision to a general lockdown.

As mentioned earlier, we focus on the response of exchange rate and stock market prices to the change in domestic number of COVID-19 cases and deaths in China and Italy.

Normal Stress Regime **High-Stress Regime**

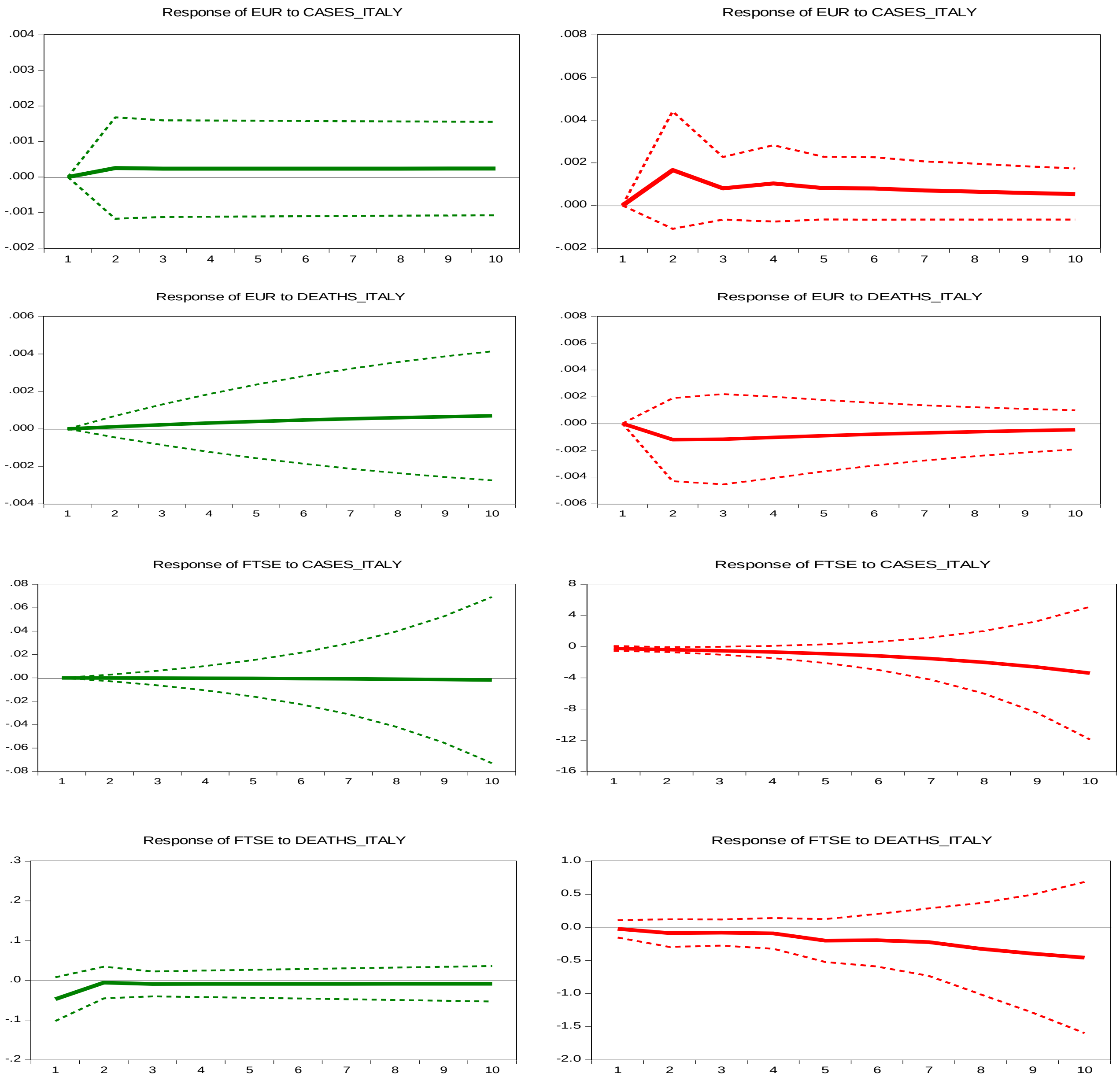


Figure 5. Impulse Response Functions (Italy)
Source: Research finding.

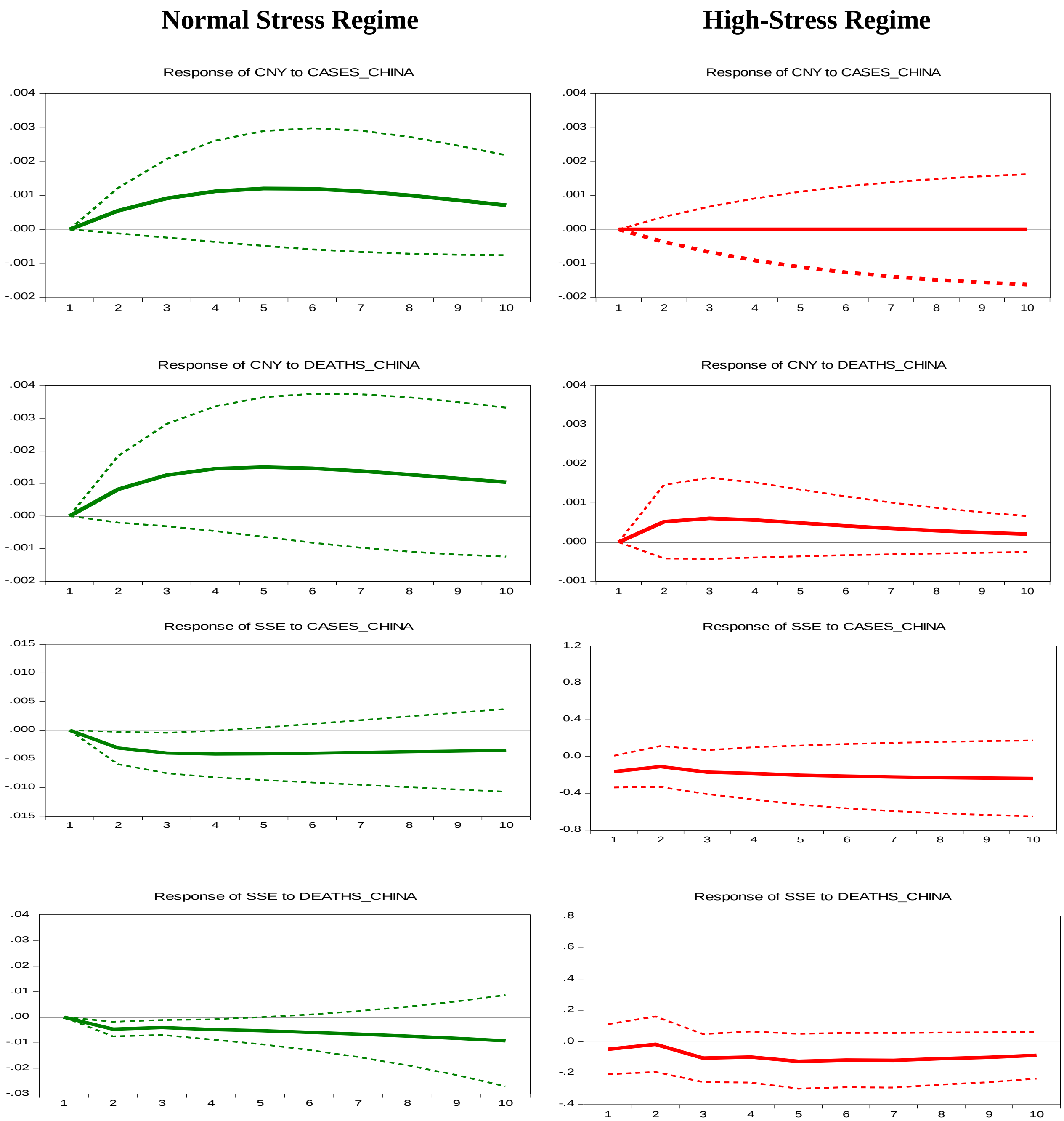


Figure 6. Impulse Response Functions (China)

Source: Research finding.

To examine whether COVID-19 uncertainty can explain fluctuations in China and Italy's stock market prices, we performed impulse response functions (IRF) of exchange rates and stock prices to a positive one deaths and cases shock in normal stress regime (1) and high-stress regime (2). Moreover, following a shock, the IRFs have the possibility of indicating the required period for a variable to converge to its equilibrium state. Figures 11 and 12 depict the results. In general, it is appeared a nonlinear response from the stock prices and exchange rate following any variation in each COVID-19 indicator. Volatility in national currencies initially increased (especially in the first three months) but faded out with the evolution of the crisis.

For Italy (Figure 11), positive one-unit deaths and disease shock led to positive stock prices. The impact of shocks on FTSE is within zero in the normal stress regime and manifests a negative reaction in the high-stress regime. The effects of the confirmed number of deaths and cases in the high-stress regime are higher than in the normal stress regime. For the Euro, we show slight variation and return to equilibrium in the 10th period. This result can be explained by the fact that the EURO is conditioned by the European Union which is a strong economy.

For China (Figure 12), reactions of CNY/USD and SSE are not the same. In the first regime the impact of COVID-19 on CNY does not last and returns to zero slightly faster in the high-stress regime. However, for SSE share prices we highlighted a negative impact for both normal and high stress regimes. China is considered an industrial superpower so it holds a very large foreign exchange reserve, mainly dollars, compared to the rest of the world, which can explain the strength of the Renminbi’s weighted USD exchange rate. However, the stock prices were affected all over the world (Liu et al., 2020).

Empirically, these findings are from several studies. For instance, the work of Xu (2021) showed that health crisis pandemic uncertainty negatively affects the stock markets. However, in the case of Canada, the stock market shows asymmetric responses. In addition, Rahman et al. (2021) found a negative stock market reaction to COVID-19. Liu et al. (2020) highlighted that Asian stock markets suffered from an immediate slowdown when the pandemic occurred. Adopting the same point of view, Gunay (2020) outlined that in case of a structural break in volatility, the Chinese stock market converge earlier to its equilibrium state compared to other countries. Apart from that, Ashraf (2020) found that in general, the response of stock markets to the increase of COVID-19 confirmed cases was negative and that this reaction was higher during the early days.

4. Conclusion

This paper provides new empirical evidence of the impact of COVID-19 on stock prices in Italy and China. The used framework is based on two steps. First, we used the Markov Regime Switching model to identify the nature of the stress period. Thus, we distinguished two regimes: The normal stress regime and the High stress regime. Second, we used the Bayesian Threshold Vector Autoregression Model which allows us to set a transition threshold between the two regimes.

This analysis reveals interesting implications. On the one hand, these findings are very important for policymakers to predict COVID-19 pandemic effects and help in policy perception of fighting against it. When the number of COVID-19 cases and deaths reach the estimated Threshold values, Italy and China can avoid switching to the high-stress period and maybe the decision to a general lockdown. On the other hand, the main conclusion drawn through the IRF's is that the COVID-19 pandemic has no/weakly impact on Chinese and Italian national currencies but can negatively influence stock market prices.

Finally, we should consider this framework for the policy reassessment according to the estimated Thresholds to address the future enhanced COVID-19 risks. However, this work is still incomplete since it does not take into consideration the socio-economic and environmental conditions of affected countries, an issue left for future research.

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Appendix 1

Table A1. Stock Index and the Date of Confirming COVID-19 in China and Italy

Countries	Stock index	The day when 1st COVID-19 case was confirmed
China	-Chinese yuan renminbi (CNY) -Shanghai Stock Exchange (SSE)	Dec. 1, 2019
Italy	-Financial Times and Stock Exchange (FTSE 100) -EURO	Jan. 31, 2020

Source: Ashraf (2020).

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