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Timing differences in the impact of Covid-19 on price volatility between assets[☆]

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ABSTRACT

We empirically examine the impacts of Covid-19 on asset price volatilities by focusing on the timing. This paper has three contributions. First, we propose a new Covid-19 dependent regime-switching volatility model for the examination. Second, results show a shift to a higher price volatility regime from a lower one for financial assets and commodities after late February 2020 when Covid-19 spread all over the world, but the timing of the impacts varies from immediate timing for the S&P 500, the FTSE 100, the COMEX gold and silver futures to the delayed timing for the ICE Brent crude oil futures followed by the timing for the ICE UK natural gas futures. Third, we find the sensitivity of Covid-19 information to the regime switch differs between financial assets and precious metal ones which have the immediate impacts: the infection speed, i.e. the changes in the number of Covid-19 infected individuals, enhance the impacts on the tendency to a high price volatility regime for the S&P 500 and the FTSE 100; both the infection speed and the number of the deaths mitigate those impacts for the gold and silver futures, respectively during a turmoil period due to Covid-19, suggesting that the gold and silver markets are functioning as risk-hedging safety assets alternative to financial assets during Covid-19 turmoil.

1. Introduction

On 22 November 2019, the first case of viral pneumonia of unknown cause was confirmed in Wuhan, China, and Covid-19 quickly spread to every corner of the world with the global human flow (see Fig. 1). According to a count by Johns Hopkins University, the number of people infected with the new coronavirus exceeded 100 million worldwide on 27 January 2021. Covid-19 epidemic will naturally have an impact on any asset value we possess. The spread of this infection will place enormous restrictions on economic activity, which will be reflected in asset price movements. The research question in this paper is how Covid-19 has affected the value of different asset classes, in particular price volatilities and what the differences are in the classes.

Research on the impact of Covid-19 on financial and commodity markets is accelerating (Zaremba et al., 2020; Zhang et al., 2020; Baek et al., 2020; Mazur et al., 2021; Sharif et al., 2020; Dutta et al., 2020; Akhtaruzzaman et al., 2021). In particular, recent research provides an analysis of the impact of Covid-19 that incorporates information on the spread of Covid-19, such as the number of infections and deaths (Ashraf, 2020; Xu, 2021; Baig et al., 2021). Like these studies, it is important to study the direct impact of the increase or decrease in the number of Covid-19 cases and deaths on asset prices. However, since the expansion

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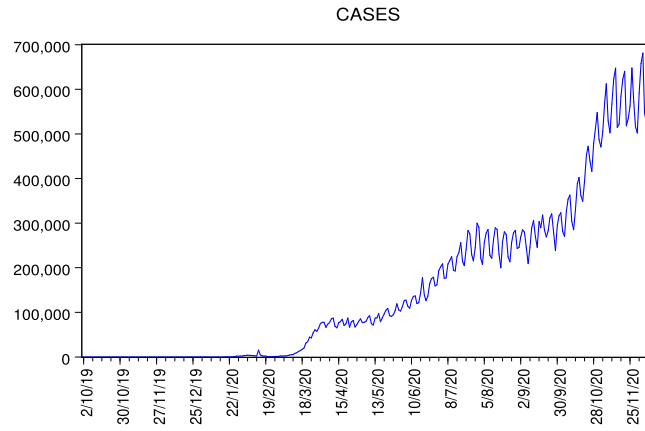


Fig. 1. The Number of New Covid-19 Cases Worldwide.

of Covid-19 will lead to significant changes in people's behaviour, we expect asset prices to transit to different regimes and these changes will not be directly influenced by Covid-19, rather the impact will be embedded in the transition probabilities as an idea of the modelling. From this point of view, the previous studies do not use a regime switching model in which the number of infected people influences regime changes. In addition, they do not use various asset class prices other than stock prices to discuss the timing of regime switching. Therefore, this study attempts to find answers to the following research questions: What is the timing of the impact of Covid-19 shocks on asset price volatility and how does it differ across asset classes?; What is the impact of Covid-19 related variables on the transition probabilities of asset price volatility due to Covid-19 shocks, and how does it differ across asset classes? To address the answers, we empirically examine the impact of Covid-19 on comprehensive asset prices by proposing a new Covid-19 dependent regime-switching volatility model. The motivation for conducting this research is to fill a gap in existing research by gaining new insights into the impact of Covid-19 on asset price volatility in the process of solving the research questions.

This paper is organised as follows. Section 2 proposes a regime-switching volatility model of asset returns based on Covid-19 information. Section 3 conducts an empirical analysis to examine time differences in the impacts of Covid-19 on comprehensive asset price volatilities. Section 4 concludes and offers the direction of future research.

2. The model

The impact of Covid-19 on asset price volatilities is likely to manifest itself in the psychological impact of Covid-19 information, namely fear of the unknown. We suppose that the impact of this fear on asset prices is not direct, but is expressed as a transition between different regimes of price volatilities. Therefore, we propose a model in which the transition probabilities of Markov switching of price volatilities are affected by Covid-19 information. Here I_t is the index at time t that represents Covid-19 information. Previous empirical analysis (e.g. Baek et al., 2020) has shown that the impact of Covid-19 on price return volatilities is represented by two regimes. Following the analysis, we introduce a two regime model with different constant volatilities.¹

$$\log S_{t+1} - \log S_t = \begin{cases} C_1 + \exp(k_1)\epsilon_t, \\ C_2 + \exp(k_2)\omega_t. \end{cases} \quad (1)$$

We employ time-varying transition probabilities based on the information on Covid-19 denoted by I_{t-1} . p_{ij} represents the transition probability from state i at time $t-1$ to state j at time t .

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} = \begin{pmatrix} p_{11} & 1 - p_{11} \\ p_{21} & 1 - p_{21} \end{pmatrix} \quad (2)$$

$$p_{11} = \frac{\exp(\delta_1 + \xi_1 I_{t-1})}{1 + \exp(\delta_1 + \xi_1 I_{t-1})} \quad (3)$$

$$p_{21} = \frac{\exp(\delta_2 + \xi_2 I_{t-1})}{1 + \exp(\delta_2 + \xi_2 I_{t-1})} \quad (4)$$

This is a new model with regime-switching volatility of assets whose transition probabilities depend on Covid-19 and, to the best of our knowledge, has not been used in existing studies on the impact of Covid-19 on asset price volatility (e.g. Ashraf, 2020). The proposal of the model itself is the first contribution of this study.

¹ Note that we will confirm a geometric Brownian motion model of asset prices in Eq. (1) we use from the empirical evidence of the existence of the unit root of the log prices later in Section 3.

Table 1
Basic statistics.

	SPX	UKX	GD	SI	OIL	NG	BDIY
Mean	3173.433	6486.971	1707.900	19.754	46.995	27.656	1151.544
Std. Dev.	279.341	701.777	170.938	4.058	12.308	11.339	480.187
Skewness	-0.609	0.311	0.034	0.585	-0.027	0.002	-0.053
Kurtosis	3.505	1.751	1.656	2.102	2.158	1.548	1.698

Table 2
Augmented Dickey–Fuller tests for log prices: Null hypothesis: Log prices have a unit root; Exogenous: A Constant.

	LSPX		LUKX		LGD		LSI		LOIL		LNG		LBDIY	
	t-Stat	Pr*	t-Stat	Pr*	t-Stat	Pr*	t-Stat	Pr*	t-Stat	Pr*	t-Stat	Pr*	t-Stat	Pr*
ADF:	-1.809	0.376	-1.675	0.443	-1.034	0.742	-0.930	0.778	-1.553	0.506	-0.739	0.834	-1.869	0.347
Lev. 1%	-3.452		-3.451		-3.451		-3.451		-3.451		-3.451		-3.451	
5%	-2.871		-2.871		-2.871		-2.871		-2.871		-2.871		-2.871	
10%	-2.572		-2.572		-2.572		-2.572		-2.572		-2.572		-2.572	
Lag:	9		0		6		0		1		1		3	

For $i = 1, 2$

$$\frac{\partial p_{i1}}{\partial I_{i-1}} = \frac{\xi_i \exp(\delta_i + \xi_i I_{i-1})}{(1 + \exp(\delta_i + \xi_i I_{i-1}))^2}. \quad (5)$$

p_{i1} is an increasing function of I_{i-1} if $\xi_i > 0$.

The impact of Covid-19 on the number of infected people is an important indicator of trends in the spread of the disease. In particular, we suppose that the infection speed at which Covid-19 is spreading, i.e. the change in the number of infected people, will be a key factor for market participants in predicting future economic activity. Therefore, the change in the number of infected people can be considered as one of the variables in looking at the impact of Covid-19 on asset prices, i.e. $I_t = \Delta C_t$.² We take the existing literature (e.g. Baek et al., 2020) one step further and model changes in the number of infected individuals as a driver of this regime switch.

3. Empirical analysis

3.1. Data

We use the S&P 500 (SPX), the FTSE 100 (UKX), the COMEX gold futures (GD), the COMEX silver futures (SI), the ICE Brent crude oil (OIL), the ICE UK natural gas futures (NG) and the Baltic Exchange dry index (BDIY).³ The data covers from 1 October 2019 to 15 December 2020, which is obtained from the Bloomberg. This data has the period when the impact of Covid-19 is strongly reflected in the various asset markets. Table 1 shows the basic statistics of the data.⁴ To justify the modelling of price returns proposed in this paper in Eq. (1), we perform a unit root test for logarithmic prices. Table 2 suggests that all log asset prices have a unit root, resulting in the log price differences that have random walk with a constant drift. The results support the model in Eq. (1). In addition, we employ the data on the daily number of newly reported Covid-19 cases and deaths worldwide which is taken from the website of European Centre for Disease Prevention and Control.

3.2. Results

By employing the Covid-19 infection speed, i.e. the change in the number of infected people as the information on Covid-19, we show the model parameter estimates for SPX, UKX, GD, SI, OIL, NG and BDIY in Tables 3, 4, 5, 6, 7, 8 and 9, respectively.⁵ These results confirmed the existence of two regimes with different volatilities for all the assets analysed from the statistical significance of k_1 and k_2 . In particular, k_1 is less than k_2 for SPX and UKX, otherwise k_1 is greater than k_2 . It implies that the volatilities in Regime 1 are less than those of Regime 2 for SPX and UKX, while the volatilities in Regime 1 are greater than those of Regime 2 for the others.

When we look at regime probabilities for SPX and UKX in Figs. 2 and 3, respectively, Regime 1 probabilities dramatically decline after late February 2020, while Regime 2 probabilities dramatically increase then. Thus, the volatilities increase after Covid-19

² In terms of the fear of the spread of Covid-19, we believe that it is the speed of the spread, rather than the number of people infected, that triggers fear in people. Therefore, our analysis uses the change of the number of infected people over time as a variable, rather than the number of infected people themselves.

³ Commodity futures employ one month rolling maturity products.

⁴ UKX, GD, SI and NG prices are positively skewed, while the other asset prices are negatively skewed. In addition, the kurtosis of SPX is much larger than that of the other asset prices.

⁵ The changes of the Covid-19 cases divided by 1000 are used for the estimation.

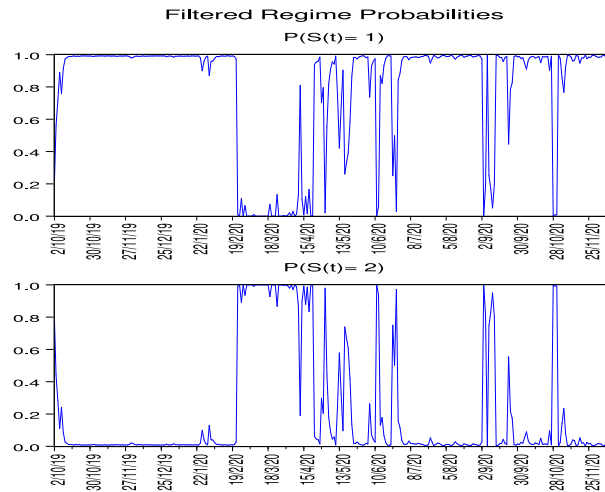


Fig. 2. Regime Probabilities for SPX: Covid-19 Case Dependent Regime-Switching Model.

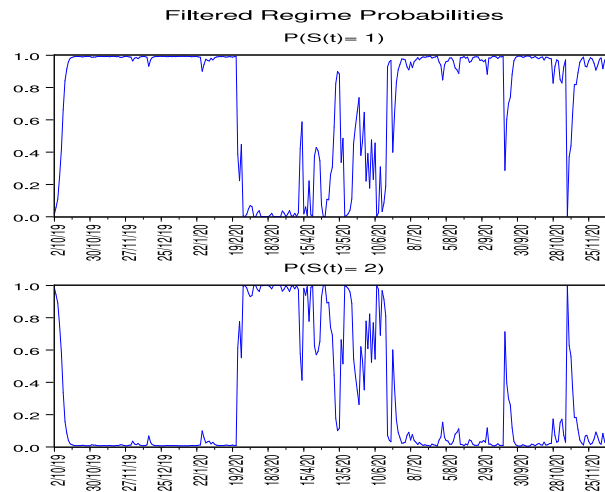


Fig. 3. Regime Probabilities for UKX: Covid-19 Case Dependent Regime-Switching Model.

shocks. For Figs. 4–7 for GD, SI, OIL and NG, respectively, in contrast to Figs. 2 and 3, Regime 1 probabilities dramatically increase after late February 2020, while Regime 2 probabilities dramatically decrease then. Therefore, we confirmed that all the volatilities for SPX, UKX, GD, SI, OIL and NG increase after Covid-19 shocks. Contrarily, BDIY in Fig. 8 has not been affected by Covid-19, despite the existence of the regime switches. We found a good like BDIY which is not affected by Covid-19.

We focus on the timing of the impacts of Covid-19 on regime probabilities. As for SPX and UKX in Figs. 2 and 3, a regime switch to a higher volatility regime occurred in late February 2020 when Covid-19 epidemic started, and the volatility has been gradually switching back to the original lower volatility regime since late April 2020. This trend can also be seen in GD and SI in Figs. 4 and 5, respectively. As in Fig. 6, OIL started its regime switch to a higher volatility regime in March 2020, later than SPX, UKX, GD and SI, and gradually switched back to its original regime around May 2020. We can see that the impacts of Covid-19 on financial assets and precious metal assets, such as SPX, UKX, GD and SI, were transmitted immediately to the markets, while the impact of Covid-19 on OIL came later than financial assets and precious metal assets, taking into account that it started to affect actual demand. Furthermore, NG in Fig. 7 showed the impact of Covid-19 even later than OIL. As can be seen, while financial assets and precious metal assets are directly affected by Covid-19, the impacts of Covid-19 on assets such as OIL and NG are timed to coincide with the impact of real demand. The results of the empirical analysis, i.e. the different timing of the impacts across assets, are, to the best of our knowledge, the second contribution of this study, as they have not been obtained from existing research results (e.g. Baek et al., 2020).

We discuss the impact of changes in the number of Covid-19 infected individuals, i.e. the infection speed, on regime switches in asset price volatilities. In the cases of SPX and UKX from Tables 3 and 4, respectively, ξ_2 is statistically significant and negative. From Eq. (5) it indicates that the increased change in the number of infected individuals contributes to maintaining the high volatility

Table 3

Parameter estimation of Covid-19 case dependent regime-switching model: SPX.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	2.368E-03	-4.784E+00	-5.655E-03	-3.228E+00	3.504	-0.009	-3.377	-0.223
Std. Err.	5.630E-04	6.993E-02	5.063E-03	1.023E-01	0.551	0.018	1.071	0.087
Loglik	931.266							
AIC	-1846.533							

Table 4

Parameter estimation of Covid-19 case dependent regime-switching model: UKX.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	2.140E-04	-4.623E+00	-1.946E-03	-3.580E+00	4.402	0.023	-4.567	-0.163
Std. Err.	7.780E-04	5.696E-02	3.287E-03	8.682E-02	1.245	0.015	1.844	0.080
Loglik	903.865							
AIC	-1791.729							

Table 5

Parameter estimation of Covid-19 case dependent regime-switching model: GD.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	-1.050E-04	-4.034E+00	1.256E-03	-5.023E+00	3.173	-0.048	-4.495	-0.089
Std. Err.	1.105E-03	8.758E-02	5.440E-04	8.966E-02	0.940	0.023	1.302	0.034
Loglik	989.344							
AIC	-1962.687							

Table 6

Parameter estimation of Covid-19 case dependent regime-switching model: SI.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	1.462E-03	-3.251E+00	8.770E-04	-4.444E+00	2.371	-0.029	-3.507	-0.094
Std. Err.	4.180E-03	7.581E-02	9.910E-04	8.675E-02	0.607	0.015	0.799	0.028
Loglik	767.230							
AIC	-1518.459							

regime because Regime 2 is a high volatility regime after Covid-19. Contrarily, in the cases of GD and SI from [Tables 5 and 6](#), respectively, both ξ_1 and ξ_2 are statistically significant and negative, while ξ_1 for SI is weakly statistical significant: since Regime 1 is a high volatility regime influenced by Covid-19, unlike SPX and UKX, from [Eq. \(5\)](#) the increase in the number of infected individuals contributes to the transition from a high volatility regime to a low one. Simultaneously unlike SPX and UKX, the increase in the number of infected individuals also contributes to maintaining a low volatility regime. We found that SPX and UKX, financial assets, maintain an increased volatility regime in response to an increase in the changes of the number of Covid-19 patients, i.e., enhance the impact of Covid-19 on the volatilities. Contrarily, GD and SI, precious metal assets, were found to reduce volatility and maintain a low volatility regime in response to an increase in the number of Covid-19 patients, i.e. mitigate the impact of Covid-19 on the volatilities. Thus, we can see that GD and SI are functioning as risk-hedging safety assets alternative to financial assets during Covid-19 turmoil. All ξ_1 and ξ_2 for commodity prices of OIL, NG and BDIY in [Tables 7–9](#), respectively, were not statistically significant. In the case of commodities, we can say that the increase or decrease in the number of infected people did not show any impact on the regime switch of price volatilities. This is not the case for more liquid assets such as SPX, UKX, GD and SI, and is more likely due to a regime switch in volatilities caused by subsequent changes in supply and demand rather than the changes in the number of infected.⁶ These results are new findings that differ from existing studies using Covid-19 related variables (e.g. [Ashraf, 2020](#)) and are the third contribution of this study.

⁶ Note that we show the results using a constant transition probability model in [Appendix A](#). For SPX, UKX, GD and SI where ξ_1 or ξ_2 was statistically significant, the AIC of the Covid-19 dependent model was smaller than that of the constant model in [Appendix A](#) except UKX, while the log likelihood for UKX regarding the Covid-19 dependent model is greater than that regarding the constant model, indicating that the Covid-19 dependent model was a better fit to the data. On the other hand, for OIL, NG and BDIY, where both ξ_1 and ξ_2 were not statistically significant, the AIC of the proposed model was larger than that of the constant model in [Appendix A](#), indicating that the constant model was a better fit to the data.

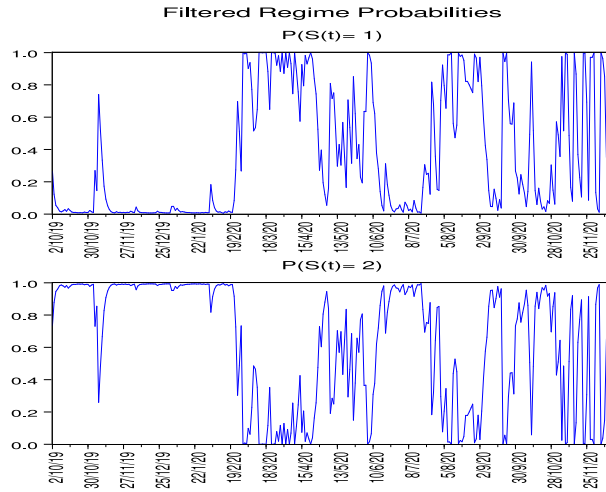


Fig. 4. Regime Probabilities for GD: Covid-19 Case Dependent Regime-Switching Model.

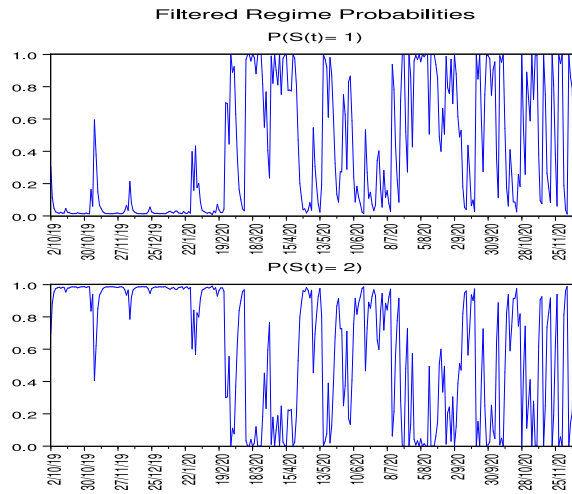


Fig. 5. Regime Probabilities for SI: Covid-19 Case Dependent Regime-Switching Model.

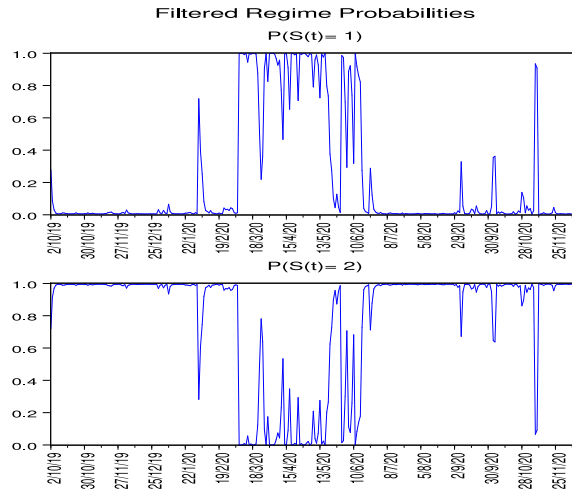


Fig. 6. Regime Probabilities for OIL: Covid-19 Case Dependent Regime-Switching Model.

Table 7

Parameter estimation of Covid-19 case dependent regime-switching model: OIL.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	-2.686E-03	-2.550E+00	1.730E-04	-3.999E+00	4.033	-0.140	-4.142	-0.001
Std. Err.	9.136E-03	9.408E-02	3.320E-03	5.594E-02	1.378	0.098	0.751	0.008
Loglik	692.147							
AIC	-1368.294							

Table 8

Parameter estimation of Covid-19 case dependent regime-switching model: NG.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	7.175E-03	-2.693E+00	-2.868E-03	-3.498E+00	3.360	0.019	-4.206	-0.002
Std. Err.	7.444E-03	8.341E-02	2.255E-03	6.355E-02	0.932	0.031	0.899	0.019
Loglik	558.664							
AIC	-1101.327							

Table 9

Parameter estimation of Covid-19 case dependent regime-switching model: BDIY.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	2.783E-03	-2.978E+00	-4.890E-03	-4.201E+00	1.827	-0.005	-1.873	0.007
Std. Err.	4.400E-03	6.908E-02	1.923E-03	1.028E-01	0.375	0.017	0.323	0.013
Loglik	633.951							
AIC	-1251.903							

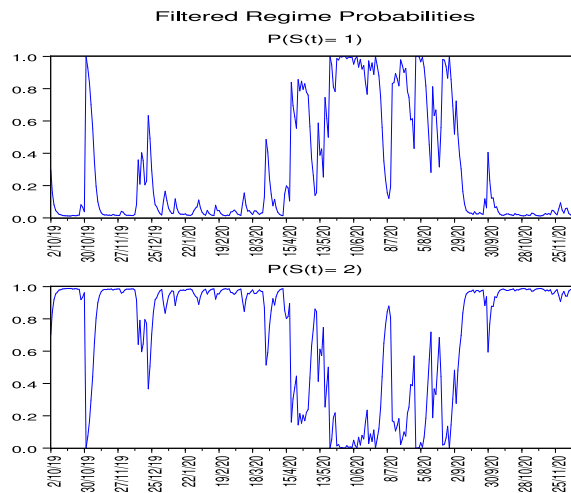


Fig. 7. Regime Probabilities for NG: Covid-19 Case Dependent Regime-Switching Model.

3.3. Further impact of Covid-19 on liquid markets

The above analysis using the Covid-19 infection speed, i.e. the daily changes in the number of newly reported Covid-19 cases, shows that financial assets of SPX and UKX and precious metal assets of GD and SI are strongly and immediately affected by Covid-19. More than the Covid-19 infection speed, the number of deaths is considered to be sufficient in itself to induce fear in people including investors. Thus, we conduct an empirical analysis that includes the number of deaths in Fig. 9 as a new variable ($I_t = D_t$) in Eqs. (3) and (4).⁷ The analysis shows that SPX and UKX in Tables 10 and 11, respectively, are not affected by the number of deaths caused by Covid-19 from the statistical insignificance of ξ_1 and ξ_2 , but GD and SI as reported in Tables 12 and 13, respectively, are affected by the number of deaths caused by Covid-19 because of the statistical significance of ξ_1 and ξ_2 , while ξ_1 for SI is weakly

⁷ The number of the Covid-19 deaths divided by 1000 are used for the estimation.

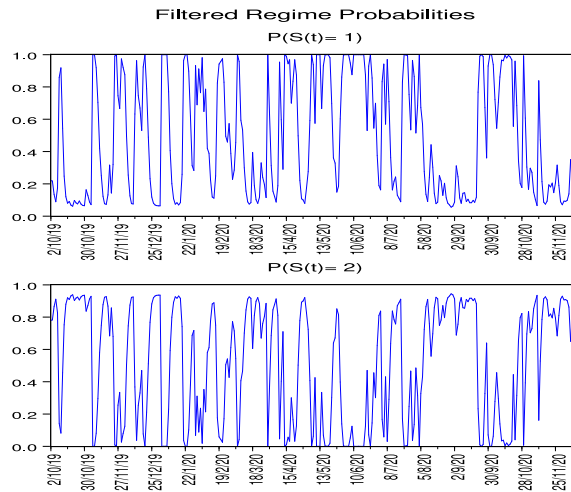


Fig. 8. Regime Probabilities for BDIY: Covid-19 Case Dependent Regime-Switching Model.

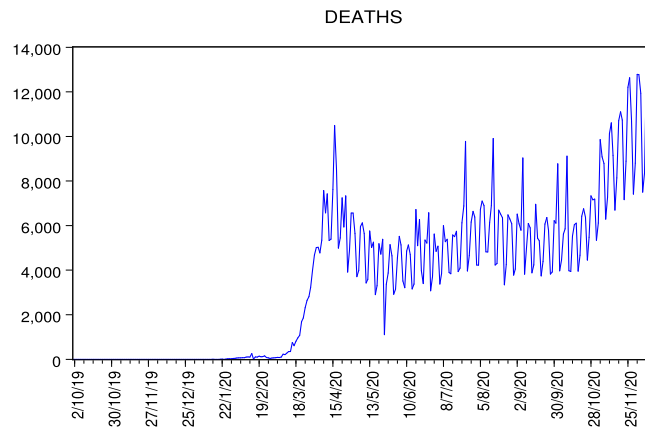


Fig. 9. The Number of New Covid-19 Deaths Worldwide.

Table 10

Parameter estimation of Covid-19 death dependent regime-switching model: SPX.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	2.300E-03	-4.869E+00	-4.016E-03	-3.305E+00	3.763	-0.115	-3.067	0.218
Std. Err.	5.640E-04	7.881E-02	4.523E-03	1.036E-01	0.647	0.111	0.929	0.192
Loglik	930.169							
AIC	-1844.339							

Table 11

Parameter estimation of Covid-19 death dependent regime-switching model: UKX.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	6.460E-04	-4.704E+00	-3.245E-03	-3.539E+00	3.512	-0.192	-3.959	0.488
Std. Err.	7.120E-04	9.341E-02	3.484E-03	1.064E-01	0.611	0.133	1.237	0.301
Loglik	904.844							
AIC	-1793.687							

statistically significant. From above, GD and SI, as real goods, tend to incorporate more information about the impact of Covid-19 on the regime change of volatility than financial assets of SPX and UKX. These results suggest that the gold and silver markets are more efficient than the stock markets during Covid-19 crisis from the point of the information inclusion. More importantly, like the

Table 12

Parameter estimation of Covid-19 death dependent regime-switching model: GD.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	-4.940E-04	-3.910E+00	1.224E-03	-5.007E+00	4.717	-1.764	-4.383	0.863
Std. Err.	2.431E-03	8.297E-02	5.100E-04	5.829E-02	1.530	0.595	0.857	0.181
Loglik	996.332							
AIC	-1976.663							

Table 13

Parameter estimation of Covid-19 death dependent regime-switching model: SI.

	Regime 1		Regime 2		TP	Matrix		
	C_1	k_1	C_2	k_2	δ_1	ξ_1	δ_2	ξ_2
Coeff.	7.220E-04	-3.276E+00	1.434E-03	-4.649E+00	1.800	-0.221	-2.998	0.615
Std. Err.	3.320E-03	7.742E-02	9.520E-04	1.223E-01	0.649	0.116	0.638	0.190
Loglik	769.065							
AIC	-1522.131							

results using the changes in the infected cases in Section 3.2 we can see that GD and SI are partially functioning as risk-hedging safety assets alternative to financial assets during Covid-19 turmoil by using the number of deaths.⁸

This study proposes a model that results in Covid-19 related variables affecting the regime-switching transition probabilities of asset price volatility, in particular the volatility of stock indices and precious metals. It is therefore not a model in which the Covid-19 related variables have a direct impact on asset price volatility. However, one may think that if there is no causal relationship between the COVID-19 and an asset price, it might weaken the argument of the timing differences in the impact of COVID-19. To answer this question, we conducted Granger causality tests reported in Table 21 of Appendix B on the Covid-19 related variables used in this subsection, namely the number of deaths, against the stock indices and the precious metal prices, which were found to be relevant for Covid-19 in this study. The results in Table 21 show that the null hypothesis that the Covid-19 related variable, the number of deaths, does not Granger cause prices is rejected at the 6, 11 and 7% level of significance for SPX, GD and SI, respectively. Therefore, it may be safe to say that the argument of no causal relationship between Covid-19 and asset prices has partially while weakly been resolved, albeit in one example. However, this partial and weak causal relationship is also one of the main reasons why this study used an indirect model in which Covid-19 related variables affect the transition probabilities of asset price volatility, rather than a direct model in which Covid-19 related variables affect asset price volatility itself.

4. Conclusions

We examined the impact of Covid-19 on comprehensive asset price volatilities by proposing a new Covid-19 dependent regime-switching volatility model. Since late February, when the spread of Covid-19 to other parts of the world occurred, we have seen a shift to a regime of increased asset price volatilities from that of lower ones by using the infection speed as a Covid-19 information variable. However, the timing of the impact varied from asset to asset. As for the stock indices of SPX and UKX, a regime switch from a low volatility regime to a high one occurred in late February 2020 when Covid-19 epidemic started, and the volatility has been gradually switching back to the low one since late April 2020. This trend can also be seen in GD and SI. OIL started its regime switch to a higher volatility regime in March 2020, later than the stocks and the precious metal futures, and gradually switched back to its original low volatility regime around May 2020. Therefore, we can see that the impacts of Covid-19 on financial assets and precious metal assets, such as the stocks and the precious metal futures, were transmitted immediately to the markets, while the impact of Covid-19 on OIL came later than the financial assets and the precious metal assets, taking into account that it started to affect actual demand. Furthermore, NG showed the impact of Covid-19 even later than OIL. As can be seen, while financial assets and precious metal assets are directly affected by Covid-19, the impacts of Covid-19 on commodities such as OIL and NG are timed to coincide with the impact of real demand. Contrarily, BDIY has not been affected by Covid-19, despite the regime switches. Thus, it is found that all goods are not necessarily affected by Covid-19. We also showed that the infection speed from changes in the number of Covid-19 infected individuals enhances the impacts on the tendency to high price volatility regime for SPX and UKX and mitigates those impacts for GD and SI, respectively during a turmoil period of Covid-19. Additionally, the analysis using the number of deaths as a new variable of Covid-19 information showed that the tendency to a higher price volatility regime for GD and SI is alleviated by the numbers of deaths unlike SPX and UKX. These results suggest that the gold and silver markets are functioning as risk-hedging safety assets alternative to financial assets during Covid-19 turmoil.

⁸ Looking at the goodness of fit of the models by minimum AIC, SPX fits the speed of infection model better, UKX fits the constant model better, and GD and SI fit the number of deaths model better. For UKX, since the log likelihood of both the speed of infection model and the number of deaths model is greater than that of the constant model, we can safely say that the fit to the Covid-19 dependent model is better than that to the constant model all for SPX, UKX, GD and SI.

Table 14
Parameter estimation of a constant TP regime-switching model: SPX.

	Regime 1		Regime 2		TP	Matrix
	C_1	k_1	C_2	k_2	δ_1	δ_2
Coeff.	2.267E-03	-4.873E+00	-3.725E-03	-3.318E+00	3.425	-2.273
Std. Err.	5.550E-04	7.517E-02	4.296E-03	9.663E-02	0.462	0.480
Loglik	929.130					
AIC	-1846.259					

In this study, we investigated the impact of Covid-19 on asset price volatility using the speed of spread of the infection and the number of deaths as variables which represent the negative impacts of Covid-19. However, there are other variables that could be considered as positive impacts, such as the number of vaccinations. These will be the subject of future research as e.g. vaccination progresses.

CRedit authorship contribution statement

Takashi Kanamura: Conceptualization, Methodology, Software, Data analysis, Writing - original draft, Writing - review & editing.

Appendix A. A constant transition probability model

p_{ij} represents the transition probability from state i at time $t-1$ to state j at time t .

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} = \begin{pmatrix} p_{11} & 1 - p_{11} \\ p_{21} & 1 - p_{21} \end{pmatrix} \quad (\text{A.1})$$

$$p_{11} = \frac{\exp(\delta_1)}{1 + \exp(\delta_1)} \quad (\text{A.2})$$

$$p_{21} = \frac{\exp(\delta_2)}{1 + \exp(\delta_2)} \quad (\text{A.3})$$

We show the model parameter estimates and the regime probabilities for SPX, UKX, GD, SI, OIL, NG and BDIY in Table 14 and Fig. 10, Table 15 and Fig. 11, Table 16 and Fig. 12, Table 17 and Fig. 13, Table 18 and Fig. 14, Table 19 and Fig. 15, and Table 20 and Fig. 16, respectively. For SPX all other parameters except C_2 are statistically significant in Table 14. For UKX, GD, SI, OIL and NG, all other parameters except C_1 and C_2 are statistically significant in Tables 15, 16, 17, 18 and 19, respectively. For BDIY, all other parameters except C_2 are statistically significant in Table 20. More importantly, k_1 is greater than k_2 only for GD, otherwise k_1 is less than k_2 . It implies that the volatilities in Regime 1 are greater than those of Regime 2 for GD, while the volatilities in Regime 1 are less than those of Regime 2 for the others.

When we look at Fig. 12, Regime 1 probabilities dramatically increase after late February 2020, while Regime 2 probabilities dramatically decrease then. Thus, the volatilities increase after Covid-19 shocks. For Figs. 10, 11 and 13–15, in contrast to Fig. 12, Regime 1 probabilities dramatically decrease after late February 2020, while Regime 2 probabilities dramatically increase then. From Fig. 16, it is obscure to distinguish between two regimes. Thus, the volatilities for all assets except BDIY increase after Covid-19 shocks. As for SPX and UKX in Figs. 10 and 11, respectively, a regime switch to a higher volatility regime occurred in late February 2020 when Covid-19 epidemic started, and the volatility has been gradually switching back to the original regime since late April 2020. This trend can also be seen in gold and silver futures in Figs. 12 and 13, respectively. As in Fig. 14, OIL started its regime switch to a higher volatility regime in March 2020, later than stocks and precious metal futures, and gradually switched back to its original lower volatility regime around May 2020. Therefore, we can see that the impacts of Covid-19 on financial assets and precious metal assets, such as stocks and precious metal futures, were transmitted immediately to the markets, while the impact of Covid-19 on OIL came later than financial assets and precious metal assets, taking into account that it started to affect actual demand. Furthermore, NG in Fig. 15 showed the impact of Covid-19 even later than OIL. As can be seen, while financial assets and precious metal assets are directly affected by Covid-19, the impacts of Covid-19 on commodities such as OIL and NG are timed to coincide with the impact of real demand. Contrarily, BDIY in Fig. 16 has not been affected by Covid-19, despite the regime switches. Thus, we found an example of commodities which is not necessarily affected by Covid-19. These results in this appendix are the same as the results using the Covid-19 dependent regime-switching model.

Appendix B. Granger causality tests

See Table 21.

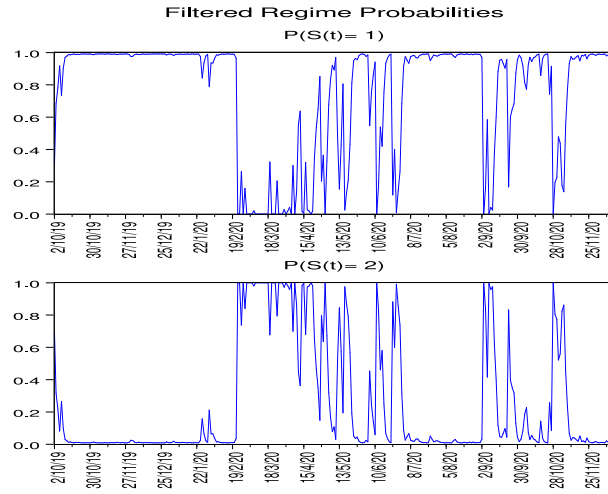


Fig. 10. Regime Probabilities for SPX: A Constant TP Regime-Switching Model.

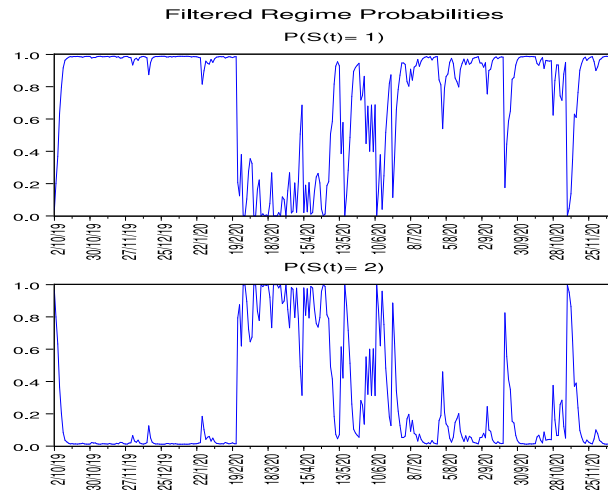


Fig. 11. Regime Probabilities for UKX: A Constant TP Regime-Switching Model.

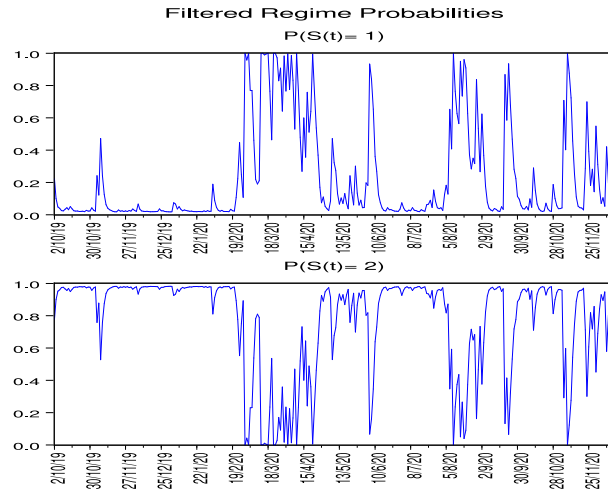


Fig. 12. Regime Probabilities for GD: A Constant TP Regime-Switching Model.

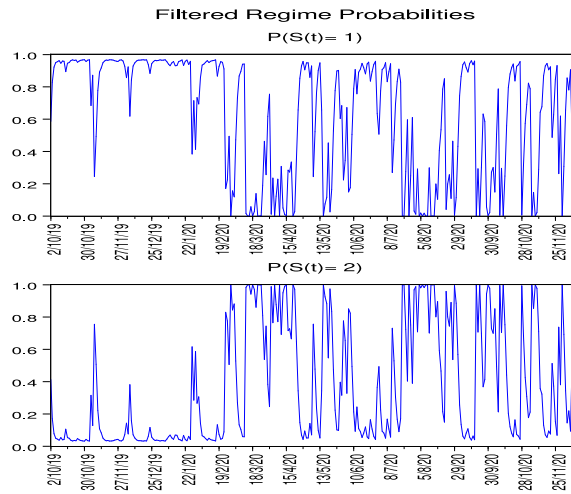


Fig. 13. Regime Probabilities for SI: A Constant TP Regime-Switching Model.

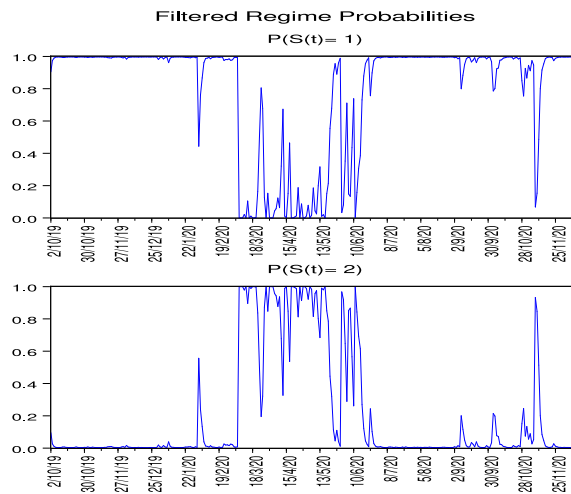


Fig. 14. Regime Probabilities for OIL: A Constant TP Regime-Switching Model.

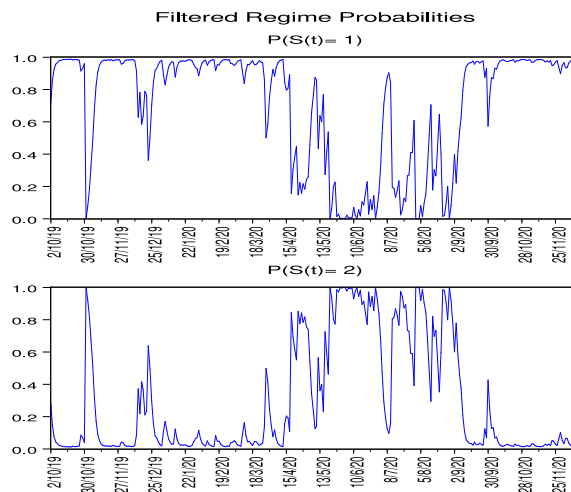


Fig. 15. Regime Probabilities for NG: A Constant TP Regime-Switching Model.

Table 15

Parameter estimation of a constant TP regime-switching model: UKX.

	Regime 1		Regime 2		TP	Matrix
	C_1	k_1	C_2	k_2	δ_1	δ_2
Coeff.	2.450E-04	-4.646E+00	-2.149E-03	-3.550E+00	3.742	-2.717
Std. Err.	8.040E-04	6.605E-02	3.488E-03	1.012E-01	0.673	0.750
Loglik	903.516					
AIC	-1795.032					

Table 16

Parameter estimation of a constant TP regime-switching model: GD.

	Regime 1		Regime 2		TP	Matrix
	C_1	k_1	C_2	k_2	δ_1	δ_2
Coeff.	-5.790E-04	-3.863E+00	1.120E-03	-4.863E+00	2.185	-3.439
Std. Err.	9.066E-03	1.226E-01	6.870E-04	1.050E-01	0.679	0.854
Loglik	985.181					
AIC	-1958.362					

Table 17

Parameter estimation of a constant TP regime-switching model: SI.

	Regime 1		Regime 2		TP	Matrix
	C_1	k_1	C_2	k_2	δ_1	δ_2
Coeff.	1.042E-03	-4.425E+00	1.233E-03	-3.225E+00	2.575	-2.009
Std. Err.	1.026E-03	1.023E-01	5.076E-03	8.313E-02	0.563	0.544
Loglik	761.890					
AIC	-1511.780					

Table 18

Parameter estimation of a constant TP regime-switching model: OIL.

	Regime 1		Regime 2		TP	Matrix
	C_1	k_1	C_2	k_2	δ_1	δ_2
Coeff.	4.210E-04	-3.974E+00	-3.679E-03	-2.539E+00	4.596	-3.148
Std. Err.	1.336E-03	7.185E-02	1.224E-02	1.019E-01	1.036	0.935
Loglik	690.251					
AIC	-1368.502					

Table 19

Parameter estimation of a constant TP regime-switching model: NG.

	Regime 1		Regime 2		TP	Matrix
	C_1	k_1	C_2	k_2	δ_1	δ_2
Coeff.	-2.899E-03	-3.499E+00	7.283E-03	-2.692E+00	4.137	-3.230
Std. Err.	2.252E-03	6.510E-02	7.479E-03	8.527E-02	0.897	0.868
Loglik	558.461					
AIC	-1104.921					

Table 20

Parameter estimation of a constant TP regime-switching model: BDIY.

	Regime 1		Regime 2		TP	Matrix
	C_1	k_1	C_2	k_2	δ_1	δ_2
Coeff.	-4.914E-03	-4.191E+00	2.822E-03	-2.979E+00	1.876	-1.837
Std. Err.	1.945E-03	1.045E-01	4.388E-03	6.971E-02	0.321	0.362
Loglik	633.745					
AIC	-1255.490					

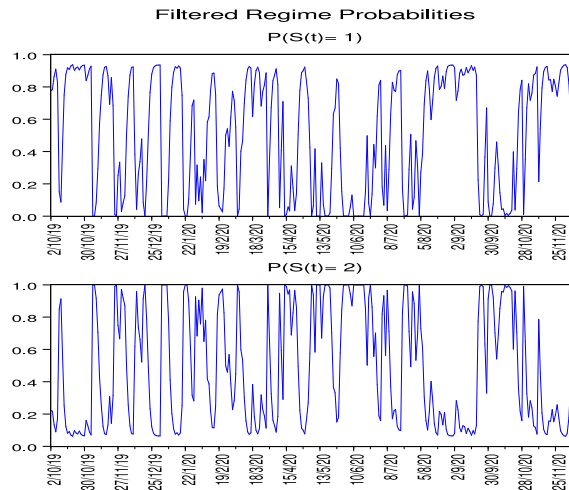


Fig. 16. Regime Probabilities for BDIY: A Constant TP Regime-Switching Model.

Table 21

Granger causality tests: Lag = 2.

Null hypothesis:	Obs.	F-Statistic	Prob.
DEATHS does not Granger Cause SPX	314	2.76	0.06
SPX does not Granger Cause DEATHS	314	0.39	0.68
DEATHS does not Granger Cause UKX	314	0.77	0.47
UKX does not Granger Cause DEATHS	314	8.47	0.00
DEATHS does not Granger Cause GD	314	2.21	0.11
GD does not Granger Cause DEATHS	314	11.65	0.00
DEATHS does not Granger Cause SI	314	2.67	0.07
SI does not Granger Cause DEATHS	314	3.11	0.05

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