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How have the dependence structures between stock markets and economic factors changed during the COVID-19 pandemic?☆

Xiyong Dong,a Li Song,b Seong-Min Yoon,c,*

a School of Economics and Management, Shanxi University, Taiyuan, China
b Taiyuan Railway Center for Disease Control and Prevention, Taiyuan, China
c Department of Economics, Pusan National University, Busan, Republic of Korea

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ABSTRACT

This study investigates how the dependence structures between stock markets and economic factors have changed during the COVID-19 pandemic using the dynamic model averaging approach. A series of economic factors such as commodity markets, cryptocurrency, monetary policy, international capital flows, and market uncertainty indices are considered. We find that the importance of economic variables and the sign and size of their coefficients are significantly different from those before the COVID-19 pandemic. The stock markets are most influenced by economic factors during the COVID-19 outbreak.

1. Introduction

The coronavirus disease 2019 (COVID-19) has brought about not only disruptions in daily life but also a crisis in real economic activities (Just and Echaust, forthcoming). The losses caused by this health crisis may be greater than earlier major crises, and some scholars call this crisis the Great Recession. Most governments adopt a range of lockdown-type policies, their economic activities are greatly restricted, and, eventually, COVID-19 may lead to mass unemployment and business failures (Zaremba et al., 2020; Zhang et al., 2020). Owing to COVID-19 being highly contagious, it quickly spread to hundreds of countries in seven regions of the world. The World Health Organization (WHO) officially declared the outbreak of COVID-19 as a global pandemic on March 11, 2020.

The COVID-19 pandemic has severely impacted financial markets and made them very vulnerable, as evidenced by one of the most dramatic stock market crashes in history in March 2020 (Mazur et al., forthcoming). At the same time, the outbreak of COVID-19 has also changed the trends of other macroeconomic variables. For example, oil prices drop sharply and gold prices rise for a long time after

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* Corresponding author at: Department of Economics, Pusan National University, 2, Busandaehak-ro 63beon-gil, Geumjeong-gu, Busan, 46241, Republic of Korea.
E-mail addresses: xydong@sxu.edu.cn (X. Dong), lilly_Song@126.com (L. Song), smyoon@pusan.ac.kr (S.-M. Yoon).

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the COVID-19 outbreak. To stimulate economic recovery, the U.S. government adopted a looser monetary policy. Various uncertainty indices have risen sharply as investor fears and market expectations are not optimistic. Sakurai and Kurokaki (2020) find that both upside and downside correlations between oil and the U.S. stock markets increased after the COVID-19 pandemic. Adekoya et al. (forthcoming) show that market risks associated with global stock markets can be effectively hedged by gold during this period. Li et al. (2020) indicate that the market risk index has superior predictive ability for the three European stock markets during this period. Thus, we investigate how the dependence structures between stock markets and economic factors have changed during the COVID-19 pandemic.

For this purpose, we apply the dynamic model averaging (DMA) approach developed by Raftery et al. (2010). This approach allows explanatory variables and their coefficients to change over time, which is helpful for exploring stock prices in an uncertain pandemic environment. As stock markets are increasingly affected by a wide range of economic factors during the COVID-19 pandemic, the DMA approach’s advantage that a series of explanatory variables are considered simultaneously is more suitable for capturing stock price behaviour in this period. However, existing research only focuses on the results of the importance of explanatory variables but does not provide their coefficient results (Aye et al., 2015; Naser, 2016; Wei and Cao, 2017). We present time-varying coefficient results, which can more accurately understand the dependence structures between stock markets and economic factors. Furthermore, unlike previous studies that only consider forecasting economic variables using the DMA model, we explore both the in-sample relationship and out-of-sample predictability of the influence of economic factors on stock markets (Dong and Yoon, 2019). The COVID-19 pandemic is first reported in some Asian countries (e.g., China and South Korea), then it is successively reported by some developed countries; hence, we take emerging Asian and developed stock markets as research objects.

This study contributes to the literature in three ways. First, this study is the first systematic analysis of the dependence structures between stock markets and a series of economic factors during the COVID-19 pandemic. Second, owing to different outbreak times, we focus on the impact of the outbreak point on the emerging Asian and developed stock markets. Third, we explore not only the importance of economic variables, but also the changes in their coefficients, enabling us to identify the variables that have a hedging effect and those that have a stimulating effect on stock markets.

2. Methodology

Although the time-varying parameter (TVP) model allows the coefficients of explanatory variables to change, it does not allow explanatory variables used in the model to change with time. Fortunately, Raftery et al. (2010) provide the DMA model, which can solve the above problems. The DMA model can be written as:

\[ y_t = x_t^{(k)} \beta_t^{(k)} + \varepsilon_t^{(k)}, \]  

\[ \beta_{t+1}^{(k)} = \beta_t^{(k)} + \eta_t^{(k)}, \]  

where \( y_t \) is the emerging Asian and developed stock returns, \( x_t^{(k)} \) denotes a vector of economic factors, and \( \beta_t^{(k)} \) denotes a vector of coefficients. The innovation term \( \varepsilon_t^{(k)} \) is \( N(0, V_t^{(k)}) \) and \( \eta_t^{(k)} \) is \( N(0, W_t^{(k)}) \). The superscript \( k = 1, \ldots, K \) denotes a specific predictor set; if there are \( m \) explanatory variables, there can be \( K = 2^m \) different forecasting models (Koop and Korobilis, 2012). Thus, both the explanatory variable vector \( x_t^{(k)} \) and the state vector \( \beta_t^{(k)} \) are different for each model, which allows both explanatory variables and its parameters to vary over time.

The evolution can be determined by a \( K \times K \) transition probability matrix, \( P \), with elements \( P_{ij} = \Pr(L_i = t | L_{i-1} = j) \). To achieve a feasible computation of \( P \), we use the approximations proposed by Raftery et al. (2010) that involve two forgetting factors, \( \alpha \) and \( \lambda \).

The parameter prediction equations using the Kalman filter obtain \( \beta_t^{(k)} \) using all information up to time \( t - 1 \):

\[ \beta_{t+1}^{(k)} \mid_{t-1} \sim N \left( \beta_{t-1}^{(k)}, S_t^{(k)} \right), y^{t-1} = \{ y_1, \ldots, y_{t-1} \}, \]  

\[ S_t^{(k)} = \frac{1}{2} \Sigma_{t-1|t-1}^{(k)}, \]  

where formulae \( \beta_{t-1}^{(k)} \) and \( \Sigma_{t-1|t-1}^{(k)} \) depend on \( V_{t}^{(k)} \) and \( W_{t}^{(k)} \). Also, \( \lambda \) denotes the forgetting factor with \( 0 < \lambda \leq 1 \). The value of the forgetting factor determines how rapidly explanatory variables and parameters evolve. To avoid applying the Markov chain Monte Carlo (MCMC) method, Eq. (4) introduces a forgetting factor, \( \lambda \), that prevents the model from estimating \( W_{t}^{(k)} \).

The model prediction equation using the Kalman filter is defined as:

\[ \pi_{t|t-1,k} = \frac{\pi_{t-1|t-1,k}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}}, \]  

where \( \alpha \) is the other forgetting predictor with \( 0 < \alpha \leq 1 \) and is interpreted in a similar manner to \( \lambda \).

Finally, the DMA obtains the final result at each point by taking the weighted average of all possible models according to these probabilities, \( \pi_{t|t-1,k} \). The DMA framework is computed as:
3. Data

The objective of our paper requires that data be taken for stock prices and economic factors at daily frequency; the data sample covers the period from May 1, 2018 to December 31, 2020.\footnote{To adapt to the time series given previously, the calculation process of the DMA model requires the length of the burn-in period. Hence, the results of observations in 2018 will be discarded, which ensures the accuracy of the empirical results. Moreover, the results from 2019 to 2020 can help us compare changes in the dependence structures before and during the COVID-19 pandemic.} This paper uses emerging Asia (EM_Asia)\footnote{The MSCI emerging Asia index includes nine markets: China, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Taiwan, and Thailand.} and global developed stock market indices, the data are extracted from the Morgan Stanley Capital Index (MSCI) database, and we choose the MSCI world index (World)\footnote{The MSCI world index contains 23 markets: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, and the United States.} to represent global developed stock markets.

The economic factors used are listed in Table 1. Due to the financialization of commodity markets, we consider two influential commodity markets (i.e., WTI and gold). The investment asset nature of cryptocurrency is becoming increasingly apparent; we also explore the hedging effect of bitcoin on stock markets. The Federal Reserve announced a zero-percent interest rate policy and unlimited quantitative easing (QE) programme in March 2020 (Zhang et al., 2020). This paper investigates the potential influence of policy intervention on stock markets. Considerable international capital flows will affect the changes in stock prices. Thus, we consider U.S. dollar (USD) index and select the TED spread as a proxy for global capital liquidity pressure (Chen and Semmler, 2018). COVID-19 has further exacerbated the uncertainty in financial markets. The U.S. economic policy uncertainty index (EPU) (Baker et al., 2012)
and implied volatility of the S&P 500 index (VIX) are considered. Owing to stationarity considerations, the log first difference is taken for all stock prices and economic factors. Since the prices of the WTI contract 1 fell to a negative level on April 20, 2020, and negative prices cannot be used for the log first difference, we select the WTI contract 2, which has remained at a positive level. To support the use of the WTI contract 2 instead of the WTI contract 1, we compute the correlation between these two contracts and find a high correlation of 0.91.

4. Empirical results

The empirical results are divided into four subsections. First, we compare the performance of models with different forgetting factors. Second, we present the expected sizes of variables in the models. Third, we provide evidence of variables that are important indicators for stock markets and regression coefficient results for all variables. Finally, out-of-sample predictability results are presented.

4.1. Model performance

The forgetting factors are responsible for how the previous estimations are remembered by the process for the current prediction in the time-varying coefficient framework, so that the instability of the coefficients can be controlled (Drachal, 2016). To assess the
performance of the models with different forgetting factors ($\alpha = 0.095 - 0.099 = \lambda$), we apply the root mean squared error (RMSE) and the mean absolute error (MAE). Fig. 1 presents the results of comparing different models. The RMSE and MAE results are relatively small when the DMA model selects a larger value of the forgetting factor, which proves that the DMA model with $\alpha = 0.99 = \lambda$ achieves better performance.

4.2. Expected sizes of variables

Fig. 2 shows the time-varying expected sizes of variables included in the DMA model with $\alpha = 0.99 = \lambda$. The emerging Asian stock markets are more affected by economic factors after the end of 2019 and global developed stock markets are more affected by

4 When one or both forgetting factors are 1, the DMA model transforms into a special case (i.e. the TVP and Bayesian model averaging (BMA) model). However, these models do not allow both the explanatory variables and their coefficients to change over time together; here we do not evaluate the performance for these models.
economic factors after mid-March 2020, which means that the outbreak of the COVID-19 pandemic has made financial markets more vulnerable. Asian markets react relatively quickly to the impact of economic factors because of the earlier outbreak in this region. Furthermore, the number of variables gradually decreases for developed markets during the COVID-19 pandemic, indicating that in the early stages of the pandemic the market is the most sensitive and investors are the most feared.

4.3. Time-varying parameters and coefficients

Although the DMA model with $\alpha = 0.99 = \lambda$ provides relatively good results, we present time-varying parameters and coefficients for all combinations of $\alpha = \{0.99, 0.98, 0.97, 0.96, 0.95\}$ and $\lambda = \{0.99, 0.98, 0.97, 0.96, 0.95\}$. The forgetting factors with a relatively slow rate make the coefficients change smoothly, while forgetting factors with a relatively fast rate cause the coefficients to change rapidly (Koop and Korobilis, 2012). However, the results with different forgetting factors follow the same paths over time, implying that conclusions about roles of explanatory variables and changes in their coefficients are very robust.

Fig. 3 shows the relative variable importance of EM_Asia for the current period (H = 0). All variables included in the model change
over time, which provides important evidence to support using the DMA model. The role of economic factors becomes stronger during the COVID-19 pandemic, except for BIT, implying that influence of economic factors on stock markets has changed significantly. As bitcoin trading is restricted by policies and market levels in many emerging Asian markets, the role of bitcoin in these markets has not improved. Also, the IR, TED, and VIX variables have a stronger relationship with emerging Asian markets than do other variables, indicating that the information transmission mechanism of these variables is faster and stronger.

Fig. 4 demonstrates the relative variable importance of World (H = 0). Because of different outbreak times, the role of economic factors reaches a peak in mid-March 2020. However, economic factors rise faster and steeper than emerging Asian markets, indicating that the response of developed markets is more pronounced. After the outbreak, their role falls back, because the pandemic becomes normal and market confidence begins to recover. During the COVID-19 outbreak, regardless of the values of the forgetting factors, most results tend to be consistent and concentrated, which proves the accuracy of our results.

Fig. 5 shows the expected values of regression coefficients of EM_Asia (H = 0). The coefficients of the WTI and gold are negative at the end of 2019 and early 2020, indicating that oil and gold markets have a safe-haven effect against stock markets when the Asian market pandemic starts and provide an extra benefit to investors. Conversely, the hedging effect of BIT on emerging Asian stock
markets is not obvious due to the low level of development of cryptocurrencies in these markets. Moreover, the coefficients of the IR are negative for emerging Asian stock markets after mid-March 2020, implying that the U.S. loose monetary policy generates financial market liquidity, which then stimulates the recovery of emerging Asian stock markets. During the COVID-19 outbreak, the USD and stock markets face serious downward pressure at the same time. Although the USD usually shows negative coefficients because of the ‘stock-oriented’ model of exchange rates (Branson, 1983; Reboredo et al., 2016), it is not a safe-haven asset against emerging Asian stock markets in this period. The coefficients of the TED and VIX are negative after the outbreak, indicating that tighter financial market liquidity and stock market volatility risk increase market uncertainty, thereby affecting changes in investor sentiment, which then leads to investors seeking to sell stock assets perceived as risky under the ‘flight-to-quality’ effect (Dong et al., 2020).

Fig. 6 shows the expected values of regression coefficients of World (H = 0). Since the recession caused by the pandemic will simultaneously result in decreases in both oil and stock prices (Sakurai and Kurosaki, 2020), the coefficients of the WTI are positive in March 2020, indicating that oil markets do not have the safe-haven feature against developed stock markets. Compared with emerging Asian stock markets, gold and BIT show a better safe-haven effect on developed stock markets, because the gold and cryptocurrency markets in these countries are more mature. The U.S. interest rate policy stimulates the recovery of developed stock markets and the
USD does not have a safe-haven effect during the COVID-19 outbreak; nevertheless, the stimulus effect of interest rate is not obvious in the long term. As regards the TED, EPU, and VIX variables, their negative shocks on developed stock markets have become significantly stronger during the pandemic, and developed stock markets are more affected by market uncertainty as the COVID-19 begins. In particular, the negative impact of the EPU variable keeps increasing, indicating that developed markets are more strongly impacted by U.S. economic policy uncertainty than emerging Asian markets. Overall, the importance of economic variables and the sign and size of their coefficients are significantly different from the previous period, implying that dependence structures between stock markets and economic factors have changed significantly during the COVID-19 pandemic.

The COVID-19 pandemic quickly spread to the world from the end of 2019, it affects not only emerging Asian and developed stock markets, but also markets in other regions. For example, stock prices in emerging Europe (EM_Europe)\(^5\) have also fallen significantly during the COVID-19 pandemic. Appendix Figs. 1 and 2 present the expected sizes of variables and the relative variable importance of

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\(^5\) Here, we choose the MSCI emerging Europe index. The MSCI emerging Europe index includes six markets: Czech Republic, Greece, Hungary, Poland, Russia, and Turkey.
EM_Europe, respectively. We find that the results of the emerging European stock markets are similar to those of the emerging Asian and developed stock markets. The emerging European markets are also greatly affected by economic factors after mid-March 2020, hence, the emerging European markets are slower to respond to economic factors than the emerging Asian markets. However, the importance of economic factors in the emerging European markets has not risen as steeply as in developed markets, implying that developed markets are most affected by these economic factors during the COVID-19 outbreak. Appendix Fig. 3 shows the expected values of regression coefficients of EM_Europe (H = 0). The change paths of the sign and size of coefficients in the emerging European markets have many similarities with those in the emerging Asian and developed markets. Nevertheless, due to the later outbreak period in Europe, oil markets cannot act as a safe-haven asset for emerging European stocks at the end of 2019. Moreover, BIT can serve as a safe-haven asset against emerging European stocks after the COVID-19 outbreak, because the emerging European cryptocurrency markets have relatively few policy restrictions compared to the emerging Asian markets.

Fig. 8. Relative variable importance of World (H = 5).
4.4. Out-of-sample predictability

Figs. 7 and 8 present the relative variable importance of World for two forecast horizons, $H = 1$ and $H = 5$. Similar to the results of $H = 0$, almost all economic factors have the strongest predictive power during the COVID-19 outbreak, indicating that transmission mechanisms of these factors become more powerful, regardless of whether referring to in-sample or out-of-sample predictability. Although we obtain the same pattern for the importance of economic variables, the results of their coefficients are very mixed because of the random walk characteristics of stock markets. For example, gold does not have a safe-haven effect on developed markets for $H = 1$; however, gold has a safe-haven effect on developed markets for $H = 5$. Since we use relatively high-frequency daily data as the research sample, the coefficient results of economic factors are random in different forecast horizons. Unlike monthly data results, these results do not provide useful information; therefore, we delete them.

5. Conclusions

This study explores how the dependence structures between stock markets and economic factors have changed during the COVID-19 pandemic. The emerging Asian and developed stock markets are most influenced by economic factors during the COVID-19 outbreak. The sign and size of coefficients of economic factors are significantly different from the previous period, proving that COVID-19 has brought about significant changes in the dependence structures between them. The importance of economic factors has risen steeply and some coefficients vary greatly in developed stock markets, indicating that developed markets are more strongly influenced by these economic factors than emerging Asian markets during the COVID-19 outbreak.

To reduce overall losses, emerging Asian market investors could hold more gold assets and developed market investors could hold more gold and bitcoin assets in their portfolios during the COVID-19 pandemic. The U.S. loose monetary policy can stimulate the recovery of stock markets when the outbreak starts; however, this policy intervention is not effective in the long term. Finally, the obvious negative dependence between market uncertainty indices and stock markets indicates that pessimistic investor sentiment has a significant impact on stock markets (Baker and Wurgler, 2006; Sun et al., forthcoming). Therefore, using social media to guide positively and pacifying investors’ panic will have a positive effect on the recovery of stock markets, especially during the COVID-19 outbreak.

CRediT authorship contribution statement

Xiyong Dong: Conceptualization, Methodology, Investigation, Funding acquisition, Writing – original draft, Data curation. Li Song: Conceptualization, Data curation, Validation, Writing - review & editing. Seong-Min Yoon: Conceptualization, Methodology, Writing - review & editing, Funding acquisition, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Fig. A1. Expected sizes of variables for EM_Europe.

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6 The results of EM_Asia are similar to those of World. To save space, their results are not provided and are available on request.
Fig. A2. Relative variable importance of EM_Europe (H = 0).
Fig. A3. Expected values of regression coefficients of EM_Europe (H = 0).
Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.najef.2021.101546.

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