7. RE-STUDY ON DYNAMIC CONNECTEDNESS BETWEEN MACROECONOMIC INDICATORS AND THE STOCK MARKET IN CHINA

Ngo Thai HUNG[1]

Abstract

This study investigates the dynamic links between the stock market and macroeconomic fundamentals in China by using monthly data ranging from 2002:M2 to 2019:M12. Based on wavelet analysis, the results reveal that interrelatedness between stock and macro-economic returns is statistically significant at low, medium, and high frequencies in this country. We find that stock returns have a positive influence on the macroeconomic variables in the long run, indicating that the stock market leads macroeconomic factors. However, macroeconomic variables impact the stock market on short term. In addition, we build the wavelet-based Granger causality test at various time scales to provide additional support to our causal association outcomes. The empirical findings of this study offer straightforward insights into investors and policymakers in connection with relationships between the stock market and macroeconomic variables in China.

Keywords: China; macroeconomic variables; stock market; Wavelet analysis; co-movement
JEL Classification: G15, E44, F31

1. Introduction

China has established itself as the world's fastest-growing emerging economy over the last two decades. China has emerged as one of the world's industrial superpowers as a result of its rapid economic growth. This development has had a significant impact on other economies around the world due to China's open-door policy in 1978 and other economic and financial reforms that began in the early 1990s and continue to this day (Abbas *et al*. 2019a; Wang and Li, 2020; Xiang *et al*. 2021). In addition, the Chinese stock market has grown dramatically since its inception in 1991 and experienced many changes, both regulatory and operational (Allen *et al*., 2013; Hu *et al*., 2013). The Shanghai stock exchange, founded in 1990 as part of the government's market-oriented economy program, was China's third most important stock exchange based on local market capitalization (Abbas *et al*., 2019b; He *et al*., 2021). There is no doubt that the trend of equity investment

[1] *University of Finance-Marketing, Ho Chi Minh City, Vietnam. E-mail: hung.nt@ufm.edu.vn.*

by local and global investors in China gradually increases due to the growing importance of global trade, national output, and size of the equity market. The intercorrelation between the stock market and macroeconomic factors is a well-debated topic in the literature among investors, financial market regulators, and policymakers in China.

As a result of recent co-movements in stock prices, the association between stock returns and the macroeconomy has received considerable attention in academic and policy circles. Because the macroeconomy underpins stock market performance, some papers look into whether stock prices may be used as a leading indicator of the real economy (Das, 2021; Tiwari *et al*., 2022; Xiang *et al*., 2021; Mishra and Debasish, 2022). Moreover, past studies have been conducted on the connection between the stock market and economic growth, concentrating on two emerging scenarios: the influence of stock prices on economic fundamentals and identifying a leading macroeconomic variable for future economic growth. Specifically, several studies argue that because economic activities reflect the movement of stock prices, economic variables can predict stock returns (Soenen and Johnson, 2001; Girardin and Joyeux, 2013; Hosseini *et al*. 2011; Lee and Brahmasrene, 2018; Wang and Li, 2020). Nevertheless, no definite conclusions have been reached regarding the form and causal direction of their relationship (Wang and Li, 2020). As a result, it is critical to investigate the relationship between the stock market and economic fundamentals.

According to Liu and Shrestha (2008), notwithstanding the increasing development in stock markets in China, there is little research on the interrelatedness between the stock market and macroeconomic indicators in China. For example, authors, among others, examined the relationship between asset prices and macroeconomic variables, which include GDP, exchange rate, money supply, consumer price index, industrial production, interest rate, etc. (Soenen and Johnson, 2001; Liu and Shrestha, 2008; Girardin and Joyeux, 2013; Abbas *et al*., 2019a; Rashid *et al*., 2019; Wang and Li, 2020). As an emerging economy, the Chinese stock market still has to expand and be regulated. It is well-known for its domination of individual investors as well as for its volatility and turbulence. As a result, it is critical to explore the time-varying relationship between the stock market and macroeconomic fundamentals in China. This study reports a step towards systematically examining the connectedness between stock market performance (Shanghai Stock Exchange Composite) and macroeconomic factors (Consumer Price Index, Money Supply, Industrial Production Index, terms of trade, retail sales, exchange rate against the US dollar, oil price, gold price, hot money, 6-months treasury bill rate, 20-years Treasury bond yield, and standard and poor 500 indexes) in China using wavelet analysis. If there is a long-run nexus, then part of the stock prices in China is also predictable. Put another way, our main research questions are: (1) Is there any causal association between the stock market prices and macroeconomic indicators in China? (2) If so, towards which directions?

This study aims to shed some light on the causal associations between the stock market prices and macroeconomic fundamentals in China, and it adds to existing research in three ways.

(1) It employs a nonlinear causality test to examine the correlation between stock prices and macroeconomic factors due to the nature of financial and economic variables. Most past empirical papers used linear relationships, which are ineffective because they do not cover specific nonlinear causal interactions. It is thus recommended to apply the nonlinear method to deal with these causality relationships. This paper uses maximal overlap discrete wavelet transform, wavelet covariance, wavelet correlation, continuous wavelet power spectrum, wavelet coherence, and wavelet-based Granger causality approaches for exploring the interaction between stock prices and macroeconomic variables, which adequately

overcomes most of the methodological issues that the existing literature suffers from (Raza *et al*., 2018).

(2) It utilizes the wavelet frameworks to decompose the data into different time frequencies, enabling us to detect the multiscale nonlinear causality associations between the pairs of the selected variables. Nevertheless, most previous scholars analyze the time series at their original level, using a cointegration that differentiates two-time scales (short- and long-term scales). Therefore, wavelet techniques help us identify and disclose the time-frequency connectedness that is still not apprehended so far and the causal association in depth.

(3) We study the linkage between stock prices and macroeconomic factors in China using monthly data instead of annual observations, which is mostly used in the past literature. Also, the data analysis based on the monthly observations will enable us to capture the interdependence more accurately in a shorter period of one year.

The findings show that, in the long run, stock returns positively influence macroeconomic variables, whereas, on short term, macroeconomic variables impact the stock market. In China, however, neutral effects exist in the long and very long run.

The rest of the paper is organized as follows: Section 2 reviews the empirical literature. Section 3 outlines the methodology of the study. Section 4 discusses the findings. Section 5 presents the conclusion and policy implications.

2. Literature Review

When examining the relationship between the stock market and macroeconomic fundamentals, it is not wrong to assert that theoretical approaches have been in reach of a consensus over the persistence of a specific connectedness between them. However, this is necessary to make the association more interesting for research. This section reviews the literature on the nexus between stock prices and macroeconomic indicators.

Soenen and Johnson (2001) empirically analyze the effects of changes in the consumer price index on industrial production and stock market returns and provide evidence of a significant positive correlation between inflation, stock returns, and real output. Using the VECM framework, Liu and Sinclair (2008) investigate the causal relationship and dynamic association between stock market performance and economic growth in China. They show unidirectional causality running from growth to stock prices in the long run and from stock prices to economic growth on short term. Based on heteroscedastic cointegration analysis, Liu and Shrestha (2008) examine the causal nexus between Chinese stock market indices and macroeconomic indicators (money supply, industrial production, inflation, exchange rate, and interest rates), and indicate that there is a significant causal nexus between stock returns and certain macroeconomic variables. In a similar vein, Girardin and Joyeux (2013) take into account the impact of volume and economic fundamentals on the long-run volatility of the Chinese stock market and reveal that macroeconomic variables and their volatility play an increasing role in the Chinese stock market, especially the CPI inflation, at the expense of speculative factors, proxied by volume. More recently, Abbas *et al.* (2019a) investigated the return and volatility connectedness between the Shanghai Stock Exchange Composite index and the set of macroeconomic variables using the spillover index technique and suggested that the directional return and volatility spillover impact is comparatively stronger from the stock market to the macroeconomic factors.

Hosseini *et al.* (2011) choose crude oil price, money supply, industrial production, and inflation rate as macroeconomic variables. The paper focuses on the relations between stock returns and macroeconomic variables in China and India using Multivariate Cointegration and Vector Error Correction Model techniques. Their findings show both long-term and short-term links between these variables in each of these two countries. Similarly, Geetha *et al.* (2011) test the dynamic relationship between seven macroeconomic variables and Malaysia, the US, and China stock markets. There is a long-run equilibrium relationship between the variables. Moreover, the result also indicates there is a short-run relation between inflation rates and China's stock market. Lai *et al*. (2013) explore dynamic relationships between macroeconomic variables and the stock markets of Taiwan, Hong Kong, and China by considering the long-run and short-run co-movements and confirm that foreign stock markets have a greater impact on the domestic market than domestic macroeconomic factors do. Gay (2016) investigates the time-series connectedness between stock market prices and the macroeconomic variables of the exchange rate and oil price for Brazil, Russia, India, and China and finds that macroeconomic variables do not significantly influence the stock market returns.

Lee and Brahmasrene (2018) study the short-run and long-run relationships between Korea Stock Exchange Market Price and macroeconomic variables (Money Supply, Industrial Production Index, Consumer Price Index, Foreign Exchange Rates, Certificate of Deposit External Shocks) using the VECM model. Their major findings confirm that there is a long-run equilibrium relationship between stock prices and macroeconomic variables in Korea. In a similar fashion, the long-run effects of macroeconomic innovations are rather insignificant under the standard ARDL model, according to Lee and Ryu (2018); however, the nonlinear model finds a negative long-run effect for every explanatory variable–market pair. Akbar *et al.* (2018) study the links between macroeconomic variables and stock market prices in Pakistan using the VECM model and report that macroeconomic indicators have a remarkable impact on the stock market. Ditimi and Sunday (2018) examine the relationship between macroeconomic fundamentals and stock prices and report that there is a long-term interrelatedness between macroeconomic factors and stock prices in Nigeria. Abbas *et al*. (2018) recently discovered a weak volatility spillover from macroeconomic indicators to the stock market at individual level for the G-7 countries. In the same vein, Abbas *et al*. (2019b) disclose the relationship between the return and volatility of the stock markets and macroeconomic factors for the G-7 countries using the spillover index approach. Their findings reveal significant interactions between the returns and volatility of the G-7 stock markets and the set of corresponding macroeconomic factors, which include industrial production, money supply, interest rates, inflation, oil prices, and exchange rates. Przekota *et al*. (2019) look at the Central and Eastern European countries to assess the interdependence between stock indices and GDP using data from 2010 to 2018. The authors suggest that the DAX index significantly influences the indexes of the Central and Eastern European countries on short term, but that they are still connected with economic activity estimated by the GDP.

Overall, the research on dynamic links between stock returns and macroeconomic factors is substantial, but it is primarily limited to economic approaches that use the short or long run, and it produces mixed results. This diversity in results suggests a need to systematically understand the various perceptions of multiscale frequency bands to take into account these intercorrelations rather than a maximum two-scale approach, since little multiscale analysis has been implemented using wavelet frameworks. The mixed results mentioned above provide a fresh and more in-depth understanding of the topic. Nevertheless, far too little attention has been paid to wavelet techniques thus far, which have a multiscale feature and give a robust opportunity to analyze series at various scales with various frequencies, as compared to only one or two scales. Several recent articles have been conducted to estimate the co-movement among time series variables using wavelet frameworks so far. For instance, Hung (2019) perfectly captures the dynamic linkages between China and four Southeast Asian countries. Raza *et al*. (2019) examine the influence of energy consumption and economic growth on environmental degradation in the United States. Mishra *et al*. (2019) offer new insights into the dynamic relationship between tourist arrivals, transportation services, growth, carbon dioxide emissions in the United States, etc.

A more recent study implemented by Abbas *et al*. (2019c) among the G7 countries considered the return and volatility of stock markets and macroeconomic fundamentals. Interestingly, the results show a strong relationship between the G7 stock markets and the macroeconomic indicators, including industrial production, money supply, interest rates, inflation, oil prices, and exchange rates. Similarly, Demir (2019) indicates that economic growth, exchange rate, FDI, and portfolio investments raise the stock market in Turkey. Celebi and Hönig (2019) disclose that some macroeconomic variables have a significant impact on stock markets in Germany. Moradi *et al*. (2021) put forward a positive relationship between inflation, unemployment rates, and stock market prices in Iran. In the US and China, Jin and Guo (2021) confirm a lead-lag relationship between these variables.

There is empirical evidence using wavelet analysis to shed light on the lead-lag nexus between oil prices and macroeconomic indicators (Das, 2021; Tiwari *et al*., 2022; He *et al*., 2021; Xiang *et al*., 2021; Mishra and Debasish, 2022). Das (2021) provides evidence of a strong relationship between oil prices, exchange rates, and stock markets in India. Pradhan *et al*. (2020) also conclude some interesting predictability patterns that vary along the spectrum of the relationship between gold and silver in this country. In particular, Tiwari *et al.* (2022) uncover that there is a strong coherence between oil prices and macroeconomic fundamentals at higher frequencies in the emerging market economies. He *et al*. (2021) uncover a negative correlation between the Turkish stock market and foreign exchange rates at different frequencies. In the Chinese context, Wang and Li (2020) document the positive association between stock returns, industrial production growth, and inflation. Xiang *et al*. (2021) investigate the relationship between oil prices and inflation and report a positive oil volatility-inflation pass-through in the short run. Mishra and Debasish (2022) confirm that bidirectional causality exists between crude oil prices and the Chinese equity market.

Apparently, wavelet techniques provide a compelling alternative that considers both the time and frequency domains at the same time. Furthermore, the wavelet approach is a robust estimator that uses signal processing, giving a single opportunity to highlight the co-movements between macroeconomic indicators and stock market returns in the time-frequency dimension. It offers more fresh insights into significant intercorrelations at various scales along the periods (Hung, 2022a; Hung, 2020). Wavelet techniques also outperform the standard OLS regression, ARDL, Granger causality or VAR, cointegration, and error correction models (Dahir *et al*., 2018; Tiwari *et al*., 2022). These approaches are currently the most common models for examining the nexus between macroeconomic indicators and stock market prices and are well-established and dominant in the field. Therefore, this paper aims to explore the dynamic linkages between macroeconomic indicators and stock market returns in China by using the wavelet transform framework, which can allow us to analyze the frequency elements of time series without losing information.

3. Methodology and Data

The wavelet model is a powerful estimation tool that uses signal processing to assess co-movements between economic series across the time-frequency dimension (Chien *et al*. 2021; Hung, 2020). It offers important insights into the possible interdependence of different scales. Through time-series spectral bands, wavelet analysis seeks information that changes over time and in the frequency dimension (Das, 2021; Pradhan *et al*., 2020). As a result, it is a more effective tool than traditional methods such as OLS, GMM, VECM Granger causality test, random effect, ARDL (Tiwari *et al*., 2022; He *et al*., 2021; Hung, 2021; Hung, 2022a; Wang and Li, 2020). Firstly, it outperforms traditional time domain and frequency domain approaches by estimating the spectral properties of a time series as a function of time. It extracts localized information from a time-frequency window and evaluates how its various periodic elements co-vary over time. Secondly, it describes the lead-lag nexus between two-time series (Jiang and Yoon, 2020). As a result, it has been widely used to estimate co-movement and causality between two variables. Thirdly, it does not require that the variables be stationary or cointegrated, which is a significant advantage of accommodating economic series regardless of stationary properties (Wang and Li, 2020; Hung, 2022b; Xiang *et al*., 2021; Mishra and Debasish, 2022). We provide a brief note on the wavelet approach in this section.

3.1 Discrete Wavelet Transform

A series $y(t)$ can be decomposed into different time scales as:

$$y(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t) \tag{1}$$

where: ϕ and ψ are the father and mother wavelet functions, respectively, denoting the smooth (low frequency) and detail (high frequency) elements of a signal. $s_J(t)$ is smooth signals and $d_J(t)$ is the detail signals.

The following is a rewrite of the time series $y(t)$:

$$y(t) = S_j(t) + D_j(t) + D_{J-1}(t) + \cdots + D_1(t) \tag{2}$$

where: the highest-level approximation $D_1(t), D_2(t), ..., D_j(t)$ are associated with oscillations of lengths 2-4, 4-8, …, $2^j + 2^{j+i}$ and $S_j(t)$ is the smooth signal, respectively.

3.2 The Continuous Wavelet Transform

We can explore the combined behavior of time series for both frequency and time using the continuous wavelet transform $W_x(s)$. The wavelet is described as follows:

$$W_x(s) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{s}}\psi^*\left(\frac{t}{s}\right) \tag{3}$$

where: the scale parameter s determines whether the wavelet can detect higher or lower components of the series $x(t)$, * denotes the complex conjugate.

3.3 Wavelet Coherence

The cross-wavelet of two series $x(t)$ and $y(t)$ can be defined as:

$$W_n^{XY}(u,s) = W_n^X(u,s)W_n^{Y*}(u,s) \tag{4}$$

where: s is the scale, * represents the complex conjugate, and u is the position.

The wavelet coherence was developed by Torrence and Webster (1999) to assess the co-movement between two time series. The squared wavelet coefficient is given by the formula:

$$R_n^2(u,s) = \frac{|S\left(s^{-1}W_n^{XY}(u,s))|^2\right)}{S\left(s^{-1}|W_X(u,s)|^2\right)S\left(s^{-1}|W_Y(u,s)|^2\right)} \tag{5}$$

where: S is a smoothing parameter for both time and frequency. $R^2(u,s)$ is in the range $0 \le R^2(u,s) \le 1$, which is similar to correlation coefficient.

3.4 Phase Difference

Because the coherence wavelet is squared, we cannot use it to illuminate the dichotomy between positive and negative reliance. As a result, we employ the phase difference technique to investigate the causation and dependency relationships between time series. The phase difference between $x(t)$ and $y(t)$ is defined by Torrence and Compo (1998) as follows:

$$\phi_{XY} = \tan^{-1}\left(\frac{\Im\{S(s^{-1}W_{XY}(u,s)\}}{\Re\{S(s^{-1}W_{XY}(u,s)\}}\right) \tag{6}$$

where: $\Im$ and $\Re$ are the imaginary and real parts of the smooth power spectrum, respectively.

3.5. The Data

This study aims to analyze the time-frequency nexus between the performance of Chinese stock markets and macroeconomic variables in this country. The data sets taken into account in this paper consist of monthly observations of all the selected variables covering the sample period from 2002: M2 to 2019: M12. All variables are from 2002 to 2019 due to the data availability of several macroeconomic indicators (Wang and Li, 2020; Xiang *et al*., 2021; Abbas and Wang, 2020). In addition, because recent years have been extremely volatile for global financial markets (Covid-19 outbreak), particularly the commodities complex, our sample concludes in December 2019. This uncertainty, which is driven by OPEC and its allies' dramatic changes in oil production (discipline in output reduction), may result in sample heterogeneity in our analysis (Lee *et al*., 2021). The stock index studied is the Shanghai Stock Exchange Composite (SSE), and the set of macroeconomic variables includes Consumer Price Index (CPI), Money Supply (MS), Industrial Production Index (IPI), terms of trade (TT), retail sales (RS), exchange rate against the US dollar (ER), oil price (OIL), gold price (GOLD), hot money (HM), 6-months treasury bill rate (TBR), 20-years Treasury bond yield (TBY) and standard and poor 500 index (S&P 500). The selection of the variables is almost similar to Liu and Shrestha (2008) and Abbas *et al*. (2019a), which is mainly based on the theoretical relevance of these variables to the stock market returns. The data comes from Bloomberg and Thomson Reuters DataStream. All the data series are converted into logarithmic form so as to obtain the return series and make our estimations more comparable.

Table 1

Descriptive Statistics of Stock Returns and Macroeconomic Variables

	SSE	S&P 500	RS	TT	HM	TBR	TBY
Mean	0.383385	0.417808	1.059681	0.021859	1.480522	0.215754	0.030423
Max	24.25259	10.23066	8.269390	32.48547	8.345753	56.24916	16.83840
Min	-28.82836	-18.56365	-6.554411	-42.68189	-6.653109	-55.96583	-18.91758
Std. Dev	7.737200	3.895982	1.584451	7.775782	1.874137	12.56373	5.434437
Skewness	-0.747512	-0.953778	-0.361539	-0.680917	-0.107414	-0.218069	0.018769
Kurtosis	5.794615	5.887564	9.275294	10.93225	5.011652	9.119305	4.316967
JB	89.986***	107.2921***	357.456***	580.278***	36.665***	337.156***	15.549***
ADF	-12.67***	-12.17***	-20.59***	-12.54***	-3.15***	-13.09***	-14.60***
	CPI	**ER**	**GOLD**	**OIL**	**IPI**	**MS**	
Mean	0.383385	0.417808	1.059681	0.021859	1.480522	1.123238	
Max	24.25259	10.23066	8.269390	32.48547	8.345753	3.128782	
Min	-28.82836	-18.56365	-6.554411	-42.68189	-6.653109	-1.279711	
Std. Dev	7.737200	3.895982	1.584451	7.775782	1.874137	0.599652	
Skewness	-0.747512	-0.953778	-0.361539	-0.680917	-0.107414	-0.037701	
Kurtosis	5.794615	5.887564	9.275294	10.93225	5.011652	5.830465	
JB	89.986***	107.292***	357.45***	580.278***	36.66***	71.8208***	
ADF	-7.92***	-7.034***	-16.15***	-11.01***	-6.389***	-3.437***	

Notes: Statistical significance at 1% level. Standard deviations (Std.Dev) and Jarque-Bera (JB).
Source: Own calculations.

Table 1 reports the summary statistics and unit root tests. All of the examined variables have positive mean values, with the S&P 500 and SSE having the highest mean returns and OIL and TT having the lowest mean returns. The riskiest series is TBR, while the least risky is MS, as according to the standard deviation. In macroeconomic returns, hot money has the largest average growth rate that is followed by retail sales, money supply, gold price, oil price, and interest rate. Terms of trade have grown negatively on average during the sample period. The standard deviations of these variables indicate that interest rates are highly volatile, while CPI is the least variable among the list of macroeconomic variables, apparently because they sometimes vary dramatically. Skewness and kurtosis coefficients suggest that both stock market prices and macroeconomic variables are far from normally distributed, which means that these series are fatter tailed. The Jarque-Bera test statistics formally confirm these outcomes. Table 1 also presents the findings of the conventional stationarity test for all considered variables. The augmented Dickey-Fuller test rejects the null hypothesis of the unit root test for all the series at the 5% significance level. These results are thus appropriate for further statistical analysis.

4. Empirical Results and Discussions

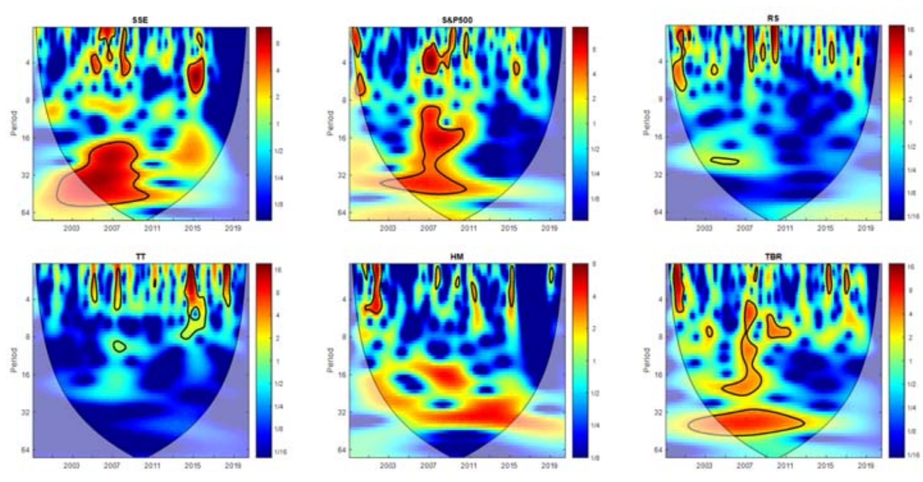
We use wavelet analysis to evaluate the dynamic connectedness between the Chinese stock markets and macroeconomic variables because wavelet frameworks are powerful techniques that enable us to estimate co-movements quickly. First, we use continuous wavelet analysis, which provides a better understanding of the interdependence between the stock market and macroeconomic factors and localized volatility over time and frequency domains, than the linear interaction technique. Second, we use wavelet coherence to look at the co-movement and lead-lag nexus structures of China's macroeconomic and stock returns. Finally, wavelet-based Granger Causality analysis is performed to illuminate the causative relationship between the variables by utilizing the time-frequency band of the wavelet transform.

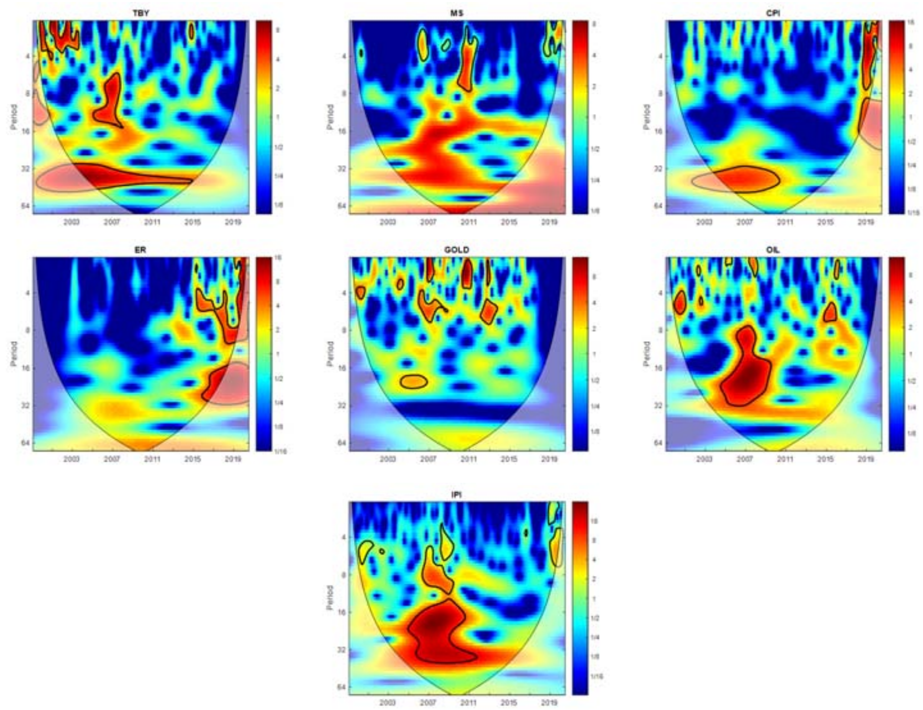
This study uses the continuous wavelet framework to decompose the data into four levels spanning different holding periods, namely short-, medium-, and long-term investment horizons. The horizontal axis covers research periods from 2002 to 2019, while the frequency bands on the vertical axis are based on monthly units ranging from 4- to 64-month scales. In other words, these levels are divided into three holding periods: 2-to-4-month scales, 4-to-16-month scales, and 16-to-64-month scales, which correspond to the short, medium, and long-term, respectively.

Figure 1 presents the continuous wavelet power spectrum of the concerned series. The continuous wavelet power spectrum demonstrates the dynamic links of the series in a three-dimensional contour plot: time, frequency, and color code. The color code for power ranges from blue (low power) to red (high power), with blue and red islands highlighting low- and high-intensity levels, respectively. Red regions depict strong variations or high-intensity movements between the series at low (high) frequency bands, while blue regions depict the weak variation of low-intensity movements.

Figure 1

The Continuous Wavelet Power Spectrum of the Selected Variables for China





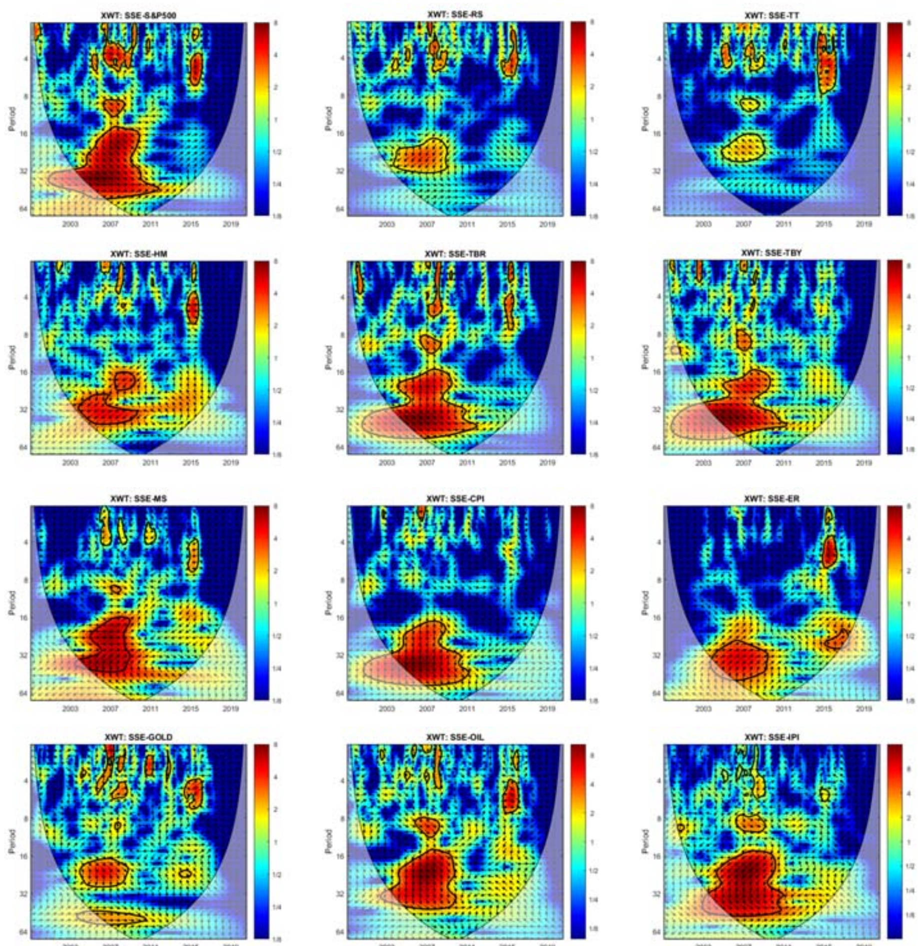
Notes: The frequency component is represented by the vertical axis, while the time component is represented by the horizontal axis; the thick back contour represents a significant region at the 5% level, and the curving black line represents a cone of impact, which exposes regions influenced by edge effects.

The intensity levels gradually go up from blue to red. The red area demonstrates that the co-movements of stock returns and macroeconomic variables in response to the shocks in China are very high. On the other hand, blue areas show the co-movements between these variables in external shocks.

The graph shows that both series of stock and macroeconomic returns have different characteristics in various time-frequency domains. We notice comparatively quite a stable variance in the long run as compared to the short run and medium run for the selected variables, except for MS and IPI. This suggests that the variance in these variables mainly occurs in the short-and medium-run. Correctly, the high deviation may be observed on all small and medium scales for the variables under consideration. Next, we move our investigation further to implement cross wavelet.

Figure 2

Cross-wavelet Transforms for the Stock Returns and Macroeconomic Factors in China



Notes: The frequency component is shown on the vertical axis, while the time component is shown on the horizontal axis. The curved black line represents a cone of impact, which displays regions influenced by edge effects. The thick back contour depicts a significant region at the 5% level, while the curved black line denotes a significant region at the 5% level. In-phase is represented by the right up and down arrows, while out-of-phase is represented by the left up and down arrows.

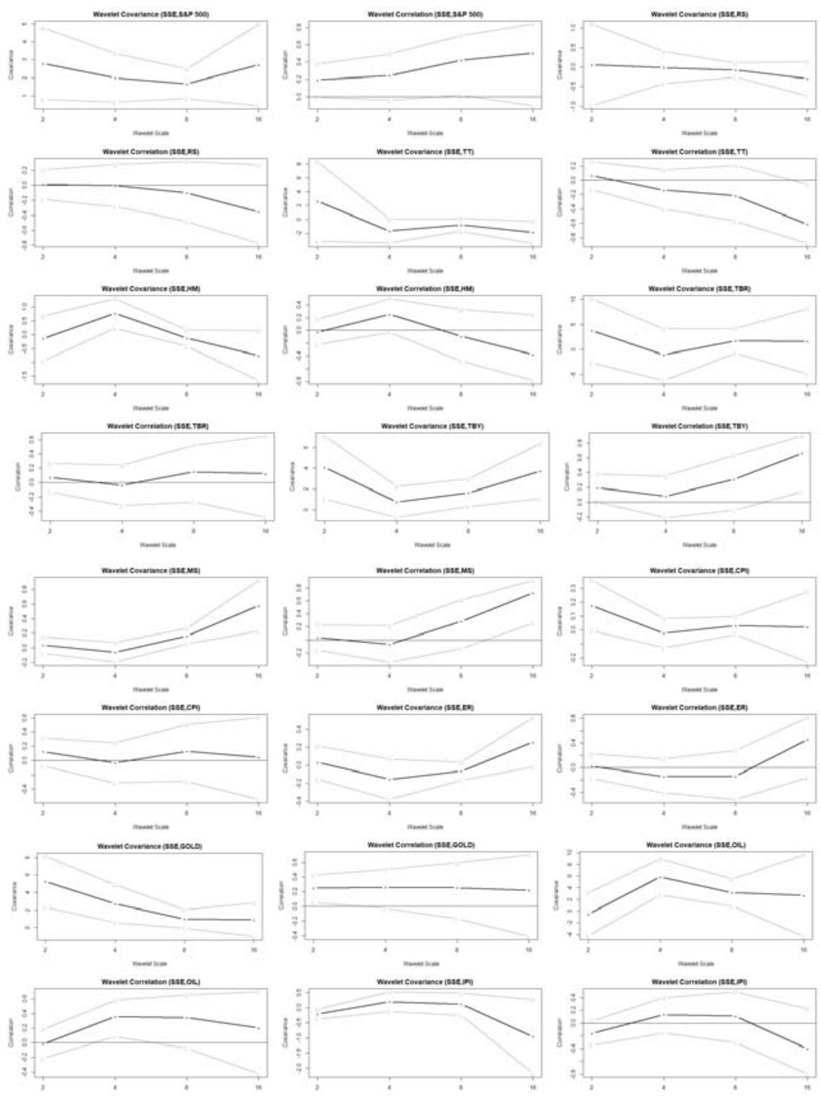
Figure 2 presents a cross wavelet transform (XWT) that reflects the local covariance between macroeconomic and stock returns at various scales and periods. The red (blue) colors illustrate high (low) power. The red (warmer) colors imply that the two series have high joint power, while the blue (cooler) colors mean that stock and macroeconomic variables have lower power. These graphs also show that covariance increased with scale, suggesting that the associations between stock market prices and macroeconomic factors were influenced more by short-term and persistent changes than long-term shocks. Overall, the cross-wavelet transform indicates that the interrelatedness between stock returns and macroeconomic factors is statistically significant at low frequencies, highlighting that the two series have different fluctuations in the short term and similar changes in the long term. Put differently, strong covariance is highlighted on 16-64-month scales around 2008-2015. Hence, the findings show that the fluctuations of indices in China witnessed underlying changes over the period shown, which implies that the Chinese economy is exposed to long-term variations. Specifically, phase differences indicate that the interdependence between stock returns and macroeconomic factors is not homogeneous across time and scales, namely, points up, down, right, and left across divergent times and scales. The arrows point to the right, indicating that the stock is leading. More accurately, the direction of the arrows at different scales and over time differs between pairs of Chinese stock returns and selected macroeconomic variables.

After decomposing the wavelet time series under investigation, we explore the interaction between the variables using wavelet covariance and correlation analysis in a given period. Figure 3 explains the outcome of the wavelet covariance and correlation between China's stock and macroeconomic returns. The graph shows positive covariance and correlation between SSE and S&P 500, TBR, TBY, CPI, GOLD, OIL in China in the short, medium, and long term. This is consistent with the findings of Geetha *et al*. (2011). By contrast, there is a negative covariance and correlation between SSE and RS, TT, and HM. Similarly, there is a negative relationship between SSE and MS and ER in the short run, but a positive correlation on long term. Therefore, the findings conclude that the increase in stock returns upsurges the macroeconomic variables in China. An intriguing outcome is that the SSE market has a considerable impact on the exchange rate and that a rise usually follows an increase in the real stock price in the Chinese Yuan Renminbi. This result supports the argument that a stock-oriented exchange rate model can explain the negative relationship between stock prices and the real exchange rate (Lee and Ryu, 2018). Furthermore, the exchange rate, stock price shocks, and macroeconomic shocks amplify each other, while stock price shocks and interest rate shocks dampen each other. These relationships show that the interest rate is the government's main tool for affecting the economy. It was discovered that the SEE market has a positive and significant impact on money supply because changes in the money supply have direct effects on portfolios as well as indirect effects on real economic activity. The implication is that changes in the stock market have the potential to affect the money market rate and, as a result, possibly truncate the capital formation drive, further slowing economic activity in China. These findings are consistent with Liu and Shrestha (2008) and Girardin and Joyeux (2013).

In the same vein, TBR and TBY appear to correlate with stock market prices positively. An increase in interest rates will encourage Chinese investors to purchase more SSE stocks rather than deposit their funds in banks or invest in other interest-bearing securities. The long-term positive nexus between stock market prices and industrial production could be explained by the fact that industrial production growth is a primary determinant of long-horizon stock returns.

Figure 3

Wavelet Covariance and Correlation between the Stock Returns and Macroeconomic Factors in China



Note: The upper and lower bound are depicted with "U" and "L" respectively at 95% confidence interval. The black dotted line depicts the covariance and correlation between the selected variables.

An increase in actual activity indicates that the firm's cash flows will improve in the future, which will likely result in an increase in the dividend paid to its shareholders. As a result, expected stock prices will rise. These outcomes are somewhat similar to those of studies such as Akbar *et al*. (2018), Ditimi and Sunday (2018), Abbas *et al*. (2019c), Celebi and Hönig (2019), and Jin and Guo (2021). Further, there is a strong positive correlation between inflation and stock market prices in China, implying that a money shock generates inflation and that increased liquidity may lower the interest rate, causing investors to shift their cash holdings to stocks in search of potential capital gains. Increases in predicted inflation, in particular, would communicate to the market possible increases in real activity and production, as well as higher stock returns (Maysami and Sim, 2001).

The empirical findings of the wavelet coherence transform are presented in Figure 4, which shows a significant connectedness between the stock returns and macroeconomic factors in China by observing lead-lag connectedness through different investment horizons. The horizontal axis illustrates the time component, while the vertical axis shows the frequency component, which is converted to months, and the color code measures the level of co-movement between the pair of indices. In addition, the wavelet coherence exhibits zones over time and scales where each pair is dependent or otherwise, associated with the local correlation ranging from 0.1 to 1.

A local correlation of 0.1 indicates that the relationships between the two variables are weak, whereas a correlation coefficient of 1 indicates a strong interrelationship. More specifically, applying phase difference, wavelet coherence has consistent results on the causality of the series. Arrows representing phase differences illustrate the direction of interdependence and cause-effect interactions. The right and left arrows highlight that the pair of variables are in-phase and out-phase, respectively. A wavelet phase that is in-phase shows that two variables have a positive association. An out-phase wavelet phase, on the other hand, suggests that two variables move in opposite directions or have a negative correlation. The right up and left down arrows indicate that the stock market is leading as the dependent variable, while the right down and left up arrows imply that the macroeconomic variables are leading as independent variables.

Table 2 summarizes the findings of wavelet coherence.

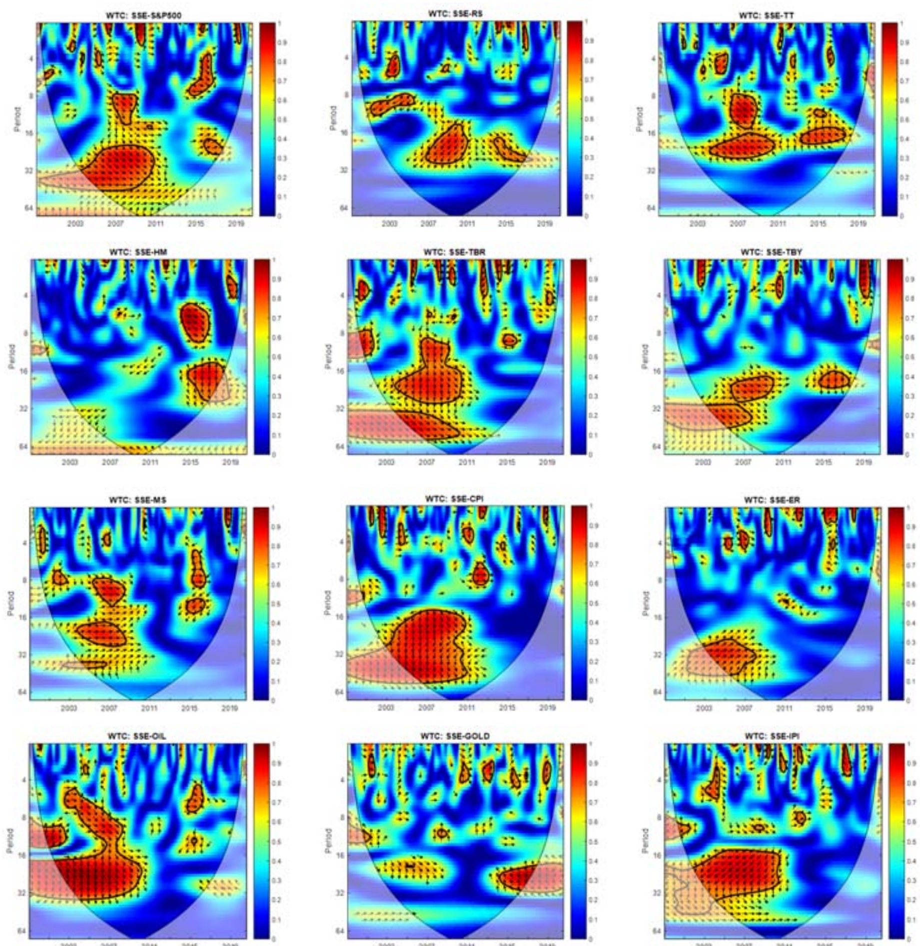
Overall, the plotting pair of wavelet coherence suggests that the Shanghai Stock Exchange Composite index and fundamental macroeconomic variables highlight significant co-movement over time and frequency domains in China. More importantly, the coherence in the index pairs (SSE-IPI; SSE-TBR; SSE-TT; SSE-CPI; SSE-MS; SSE-OIL) increases at higher frequency bands persist from about 2007 to 2015, which means that intercorrelation of these pairs sheds light on high coherence. On the other hand, the SSE-RS, SSE-HM, SSE-TBY, SSE-ER, and SSE-GOLD pairs show weak correlations over the period shown.

The wavelet coherence approach results show that in the long run, stock returns positively influence the macroeconomic variables, whereas, in the short run, the macroeconomic variables impact the stock market. Put another way, the stock price movement causes fluctuations in macroeconomic variables in China. In addition, the lead-lag nexus between stock returns and the examined individual macroeconomic indicators is quite mixed. The stock market tends to lead these macroeconomic fundamentals in the short run and lags in the long run.

This expansion was made possible by the rapid increase in investment, the effects of reforms, the positive international economic environment, and contributions, particularly from the service and manufacturing sectors.

Figure 4

Wavelet Coherence for the Stock Returns and Macroeconomic Factors in China



Notes: The frequency component is shown on the vertical axis, while the time component is shown on the horizontal axis. The thick back contour denotes a significant region at the 5% level, and the curving black line denotes a cone of impact, which displays regions influenced by edge effects. In-phase is represented by the right up and down arrows, while out-of-phase is represented by the left up and down arrows.

Table 2

Wavelet Coherence Findings Summary

Frequencies	Cross-wavelet coherence	
	SSE-S&P 500	**SSE-RS**
High frequency	$\uparrow SSE \rightarrow \uparrow S\&P500$; $\uparrow S\&P500 \rightarrow \uparrow SSE$	$\uparrow SSE \rightarrow \downarrow RS$; $\uparrow RS \rightarrow \downarrow SSE$
Medium frequency	$\uparrow SSE \rightarrow \uparrow S\&P500$	$\uparrow SSE \rightarrow \downarrow RS$
Low frequency	$\uparrow SSE \rightarrow \downarrow S\&P500$	$\uparrow SSE \rightarrow \downarrow RS$
	SSE-TT	**SSE-HM**
High frequency	$\uparrow SSE \rightarrow \downarrow TT$	$\uparrow SSE \rightarrow \downarrow HM$
Medium frequency	$\uparrow TT \rightarrow \downarrow SSE$	$\uparrow SSE \rightarrow \uparrow HM$
Low frequency	$\uparrow SSE \rightarrow \uparrow TT$	$\uparrow SSE \rightarrow \downarrow HM$; $\uparrow HM \rightarrow \downarrow SSE$
	SSE-TBR	**SSE-TBY**
High frequency	$\uparrow SSE \rightarrow \uparrow TBR$; $\uparrow TBR \rightarrow \uparrow SSE$	$\uparrow SSE \rightarrow \uparrow TBY$
Medium frequency	$\uparrow SSE \rightarrow \downarrow TBR$	$\uparrow SSE \rightarrow \uparrow TBY$
Low frequency	$\uparrow SSE \rightarrow \downarrow TBR$	$\uparrow SSE \rightarrow \uparrow TBY$
	SSE-MS	**SSE-CPI**
High frequency	$\uparrow SSE \rightarrow \uparrow MS$; $\uparrow MS \rightarrow \downarrow SSE$	$\uparrow SSE \rightarrow \downarrow CPI$; $\uparrow CPI \rightarrow \downarrow SSE$
Medium frequency	$\uparrow SSE \rightarrow \uparrow MS$	$\uparrow SSE \rightarrow \uparrow CPI$
Low frequency	$\uparrow SSE \rightarrow \uparrow MS$	$\uparrow SSE \rightarrow \downarrow CPI$
	SSE-ER	**SSE-GOLD**
High frequency	$\uparrow SSE \rightarrow \uparrow ER$	$\uparrow SSE \rightarrow \uparrow GOLD$
Medium frequency	$\uparrow SSE \rightarrow \downarrow ER$	$\uparrow GOLD \rightarrow SSE \downarrow$
Low frequency	$\uparrow SSE \rightarrow \downarrow ER$	$\uparrow SSE \rightarrow \uparrow GOLD$
	SSE-OIL	**SSE-IPI**
High frequency	$\uparrow SSE \rightarrow \uparrow OIL$; $\uparrow OIL \rightarrow \downarrow SSE$	$\uparrow SSE \rightarrow \downarrow IPI$; $\uparrow SSE \rightarrow \uparrow IPI$
Medium frequency	$\uparrow SSE \rightarrow \uparrow OIL$	$\uparrow SSE \rightarrow \uparrow IPI$
Low frequency	$\uparrow OIL \rightarrow \downarrow SSE$	$\uparrow SSE \rightarrow \downarrow IPI$

Notes: $\uparrow$ *denotes an increase in,* $\downarrow$ *denotes a decrease in,* $\rightarrow$ *denotes the variable on the left side of arrow leads the variable on the right side of the arrow.*

A higher-level relationship implies a long-term and gradually changing spillover effect on the Chinese economy. The global financial crisis of 2008 and the European sovereign debt crisis (2010–2012) had a negative impact on the Chinese market, implying that it had a short-term impact on the economy. Additionally, because of the shale oil revolution, which put downward pressure on the global price of the world stock market, the magnitude of these variables remained high until recently. After the 2008 crisis, China's macroeconomic policy encouraged economic development. The great coherency in the opposite direction in 2012 and 2016 reflects the fact that, following recovery, stock prices rise while macroeconomic factors fall. Specifically, because China is a large oil importer, the strong correlation between the economic variables and oil prices resulted from the country's rapid economic expansion. According to the overall analysis, there are progressive changes in time series such as stock returns and macroeconomic fundamentals in the Chinese economy. Market volatility caused by macroeconomic events compounds these changes. Our findings show that there is greater integration across markets when there is financial turmoil, which is consistent with previous research. Tiwari *et al*. (2022), He *et al*. (2021), Wang and Li (2020), and Mishra and Debasish (2022) also demonstrate that there is a strong coherence between stock market prices and macroeconomic indicators.

Robustness Check

For the robustness check, we use wavelet-based Granger causality tests. In this case, we use the MODWT-based "Least Asymmetric (LA) Wavelet Filter" to decompose all of the raw series into different frequencies (D1, D2, D3, D4, D5) (Daubechies, 1992). Table 3[2] shows the estimations of Granger causality across frequency ranges and time scales. The estimates offer us an opportunity to analyze whether SSE causes the change in high, medium, and low frequencies of the macroeconomic variables in China. The outcomes show a bidirectional causal association between SSE and IPI in the medium and long run. Alongside this, GOLD is found to impact SSE in the long run significantly. Specifically, results also show the unidirectional causal influence of SSE on the macroeconomic variables in the short, medium, and long term in China. Based on this new evidence, we can conclude that the co-movements in Chinese stock market prices and macroeconomic fundamentals studied using the wavelet coherence approach, as well as the results of causality tests, validate the correlation transformation.

5. Conclusion

This study discusses the intercorrelations between the stock market and macroeconomic fundamentals in China. The aim is to shed light on the lead-lag effect and mutual coherence function between the selected variables using the wavelet technique. The wavelet transform framework allows the decomposition of various series at different time frequencies. To investigate the interrelatedness between the variables, monthly data from the years 2002 (February) to 2019 (December) was used. The techniques employed on the dataset consist of wavelet-based correlation, covariance, coherence spectrum, continuous power spectrum, and wavelet-based Granger causality test.

Turning to pairwise association outcomes, we note that the interplay between stock returns and macroeconomic factors is statistically significant at low, medium, and high frequencies in China. Firstly, there is a positive covariance and correlation between SSE and S&P 500, TBR, TBY, CPI, GOLD, OIL, while negative covariance and correlation between SSE and RS, TT, and HM are found in the short, medium, and long term. Secondly, the nexus between these variables is occurring at a low frequency, which means that SSE and macroeconomic factors have different volatility on short term and similar volatility on long term. Thirdly, the wavelet coherence results show that in the long run, stock returns have a positive influence on macroeconomic variables, whereas in the short run, macroeconomic variables impact the stock market in China. Finally, we build the wavelet-based Granger causality test at different time scales to provide additional support to our interconnectedness findings.

The findings of this paper have substantial implications for investors, regulators, and policymakers in making investment decisions about investing in the capital markets because they could be critical in areas such as the design of stabilization and adjustment programs. Furthermore, the dynamic relationship between macroeconomic indicators and stock market performance in China informs a valuable tool in the literature for measuring and forecasting stock market activity (Akbar *et al*., 2018). For example, domestic macroeconomic variables significantly influence stock returns in China, which might prove helpful for portfolio

[2] *Table 3 can be viewed online at http://ipe.ro/rjef/htm.*

diversification strategies. Moreover, investors might improve their portfolio performance in individual markets by concentrating on the changes in economic risk factors (Acikalin *et al.*, 2008). During 2002–2019, the SSE was consistently determined by macroeconomic factors. Our findings suggest that investors interested in investing in China should pay closer attention to the aforementioned macroeconomic variables.

This paper also suggests that the Chinese government should guarantee the execution of prudent macroeconomic policies if the country has set out to derive the best from the stock market. Additionally, the government should look inward at the high rate of inflation because it is one of the key macroeconomic factors used to analyze the economic situation (Ditimi and Sunday, 2018). The current empirical study has short-, medium-, and long-term implications, particularly for policymakers designing financial market growth policies, retail investors and fund managers investing in capital markets, and project managers formulating capital investment decisions in emerging economies such as China. The study of the causal associations between macroeconomic indicators and stock market performance in developed and developing countries provides a valuable tool in the literature for measuring and forecasting stock market activity.

The interplay between the stock market and the macroeconomy is complicated, and it might be influenced by a variety of other factors and channels. Even though this study yielded strong empirical findings, additional research for other emerging markets is needed to capture the time-frequency dependency between crude oil prices and the macroeconomy. The wavelet approach has primarily been criticized for its bivariate properties. Although this is a limitation, it is outweighed by the method's benefits. There is still a lot of work to be done on this topic, both theoretically and empirically, such as incorporating additional variables. Multivariate techniques can be used to re-investigate this relationship. This is something we will have to look into further.

Acknowledgment: This research is funded by University of Finance-Marketing, Ho Chi Minh City, Vietnam.

References

Acikalin, S., Aktas, R. and Unal, S., 2008. Relationships between stock markets and macroeconomic variables: an empirical analysis of the Istanbul Stock Exchange. *Investment Management and Financial Innovations*, *5*(1), pp.8-16.

Abbas, G. Wang, S., 2020. Does macroeconomic uncertainty really matter in predicting stock market behavior? A comparative study on China and USA. *China Finance Review International*, *10*(4), pp. 393-427.

Abbas, G., Hammoudeh, S., Shahzad, S.J.H., Wang, S. and Wei, Y. 2019c. Return and volatility connectedness between stock markets and macroeconomic factors in the G-7 countries. *Journal of Systems Science and Systems Engineering*, *28*(1), pp.1-36. https://doi.org/10.1007/s11518-018-5371-y.

Abbas, G., Hammoudeh, S., Shahzad, S.J.H., Wang, S. and Wei, Y., 2019b. Return and Volatility Connectedness between Stock Markets and Macroeconomic Factors in the G-7 Countries. *Journal of Systems Science and Systems Engineering*, *28*(1), pp.1-36. https://doi.org/10.1007/s11518-018-5371-y.

Abbas, G., Bashir, U., Wang, S., Zebende, G.F. and Ishfaq, M., 2019a. The return and volatility nexus among stock market and macroeconomic fundamentals for China. *Physica A: Statistical Mechanics and its Applications*, *526*, p.121025. https://doi.org/10.1016/j.physa.2019.04.261.

Abbas, G., McMillan, D.G. and Wang, S., 2018. Conditional volatility nexus between stock markets and macroeconomic variables: Empirical evidence of G-7 countries. *Journal of Economic Studies*, *45*(1), pp.77-99.

Akbar, M.I.U.D., Butt, A.R. and Chaudhry, A.F., 2018. An empirical relationship between macroeconomic indicators and Pakistan stock market: 1992-2012. *International Journal of Computer Science and Network Security*, *18*(7), pp.17-26.

Al-Sharkas, A., 2004. The Dynamic Relationship between Macroeconomic Factors and the Jordanian stock market. *International Journal of Applied Econometrics and Quantitative Studies*, *1*(1), pp.97-114.

Allen, D.E., Amram, R. and McAleer, M., 2013. Volatility spillovers from the Chinese stock market to economic neighbours. *Mathematics and Computers in Simulation*, *94*, pp.238-257.

Chien, F., Sadiq, M., Kamran, H. W., Nawaz, M. A., Hussain, M. S., & Raza, M., 2021. Co-movement of energy prices and stock market return: environmental wavelet nexus of COVID-19 pandemic from the USA, Europe, and China. *Environmental Science and Pollution Research*, *28*(25), 32359-32373. .https://doi.org/10.1007/s11356-021-12938-2

Celebi, K. and Hönig, M., 2019. The impact of macroeconomic factors on the German stock market: Evidence for the crisis, pre-and post-crisis periods. *International Journal of Financial Studies*, *7*(2), 18. https://doi.org/10.3390/ijfs7020018.

Dahir, A.M., Mahat, F., Ab Razak, N.H. and Bany-Ariffin, A.N., 2018. Revisiting the dynamic relationship between exchange rates and stock prices in BRICS countries: A wavelet analysis. *Borsa Istanbul Review*, *18*(2), pp.101-113. https://doi.org/10.1016/j.bir.2017.10.001.

Das, S., 2021. The time–frequency relationship between oil price, stock returns and exchange rate. *Journal of Business Cycle Research*, *17*(2), pp.129-149. https://doi.org/10.1007/s41549-021-00057-3.

Daubechies, I., 1992. Ten lectures on wavelets: Society for Industrial and Applied Mathematics (SIAM). *Philadelphia, PA*.

Demir, C., 2019. Macroeconomic determinants of stock market fluctuations: The case of BIST-100. *Economies*, *7*(1), pp.1-14.

Ditimi, A. and Sunday, K., 2018. Dynamic interelationship between macroeconomic fundamentals and stock prices in Nigeria. *Journal of Finance and Marketing,* 2(1), pp.*50-59.* https://doi.org/10.1016/j.bir.2017.10.001.

Fernández-Macho, J., 2012. Wavelet multiple correlation and cross-correlation: A multiscale analysis of Eurozone stock markets. *Physica A: Statistical Mechanics and its Applications*, *391*(4), pp.1097-1104. https://doi.org/10.1016/j.physa.2011.11.002.

Gay, R.D., 2016. Effect of macroeconomic variables on stock market returns for four emerging economies: Brazil, Russia, India, and China. *International Business & Economics Research Journal (IBER)*, *15*(3), pp.119-126. https://doi.org/10.19030/iber.v15i3.9676.

Geetha, C., Mohidin, R., Chandran, V.V. and Chong, V., 2011. The relationship between inflation and stock market: Evidence from Malaysia, United States and China. *International journal of economics and management sciences*, *1*(2), pp.1-16.

Girardin, E. and Joyeux, R., 2013. Macro fundamentals as a source of stock market volatility in China: A GARCH-MIDAS approach. *Economic Modelling*, *34*, pp.59-68. https://doi.org/10.1016/j.econmod.2012.12.001.

He, X., Gokmenoglu, K. K., Kirikkaleli, D. and Rizvi, S. K. A., 2021. Co□movement of foreign exchange rate returns and stock market returns in an emerging market:

Evidence from the wavelet coherence approach. *International Journal of Finance & Economics*, pp. 1-12. https://doi.org/10.1002/ijfe.2522
Hu, H., Su, M. and Lee, W., 2013. Insurance activity and economic growth nexus in 31 regions of China: bootstrap panel causality test. *Romanian Journal of Economic Forecasting*, *16*(3), pp.182-198.
Hosseini, S.M., Ahmad, Z. and Lai, Y.W., 2011. The role of macroeconomic variables on stock market index in China and India. *International Journal of Economics and finance*, *3*(6), pp.233-243.
Hung, N.T., 2019. Equity market integration of China and Southeast Asian countries: further evidence from MGARCH-ADCC and wavelet coherence analysis. *Quantitative Finance and Economics*, *3*(2), pp.201-220.
Hung, N. T., 2020. Time-Frequency nexus between bitcoin and developed stock markets in the Asia-Pacific. *The Singapore Economic Review*, 1-26.https://doi.org/ 10.1142/S0217590820500691 .
Hung, N. T., 2021. Oil prices and agricultural commodity markets: evidence from pre and during COVID-19 outbreak. *Resources Policy*, *73*, 102236. https://doi.org/10.1016/j.resourpol.2021.102236.
Hung, N. T., 2022a. Biomass energy consumption and economic growth: insights from BRICS and developed countries. *Environmental Science and Pollution Research*, 1-18. https://doi.org/10.1007/s11356-021-17721-x.
Hung, N. T., 2022b. Time-Frequency Co-Movements between Biomass Energy Consumption and Human Development in Brics Countries. *Problemy Ekorozwoju*, *17*(1), pp.196-210.
Jin, Z. and Guo, K., 2021. The dynamic relationship between stock market and macroeconomy at sectoral level: evidence from Chinese and US stock market. *Complexity*, *2021*, pp. 1-16.
Jiang, Z. and Yoon, S. M., 2020. Dynamic co-movement between oil and stock markets in oil-importing and oil-exporting countries: Two types of wavelet analysis. *Energy Economi.s*, *90*, 104835. https://doi.org/10.1016/j.eneco.2020.104835
Lai, S., Cheng, T.Y., Li, H.C. and Chien, S.P., 2013. Dynamic interactions among macroeconomic variables and stock indexes in Taiwan, Hong Kong, and China. *Emerging Markets Finance and Trade*, *49*(sup4), pp.213-235. https://doi.org/10.2753/REE1540-496X4905S415.
Lee, J.W. and Brahmasrene, T., 2018. An Exploration of Dynamical Relationships between Macroeconomic Variables and Stock Prices in Korea. *Journal of Asian Finance, Economics and Business*, *5*(3), pp.7-17.
Lee, G. and Ryu, D., 2018. Asymmetry in the stock price response to macroeconomic shocks: evidence from the Korean market. Available at *SSRN* 3049923.
Lee, C.C., Lee, C.C. and Li, Y.Y., 2021. Oil price shocks, geopolitical risks, and green bond market dynamics. *The North American Journal of Economics and Finance*, *55*, 101309. https://doi.org/10.1016/j.najef.2020.101309.
Liu, M.H. and Shrestha, K.M., 2008. Analysis of the long-term relationship between macro-economic variables and the Chinese stock market using heteroscedastic cointegration. *Managerial Finance*, *34*(11), pp.744-755. https://doi.org/10.1108/03074350810900479.
Liu, X. and Sinclair, P., 2008. Does the linkage between stock market performance and economic growth vary across Greater China?. *Applied Economics Letters*, *15*(7), pp.505-508. Htt.s://doi.org/10.1080/13504850500426277
Mishra, S. and Debasish, S.S., 2022. Exploring relationship between crude oil price volatility and stock indices movement using wavelet analysis: evidence from India and China, *Vilakshan - XIMB Journal of Management*, *19*(1), pp. 69-86.

Moradi, M., Appolloni, A., Zimon, G., Tarighi, H. and Kamali, M., 2021. Macroeconomic factors and stock price crash risk: Do managers withhold bad news in the crisis-ridden Iran market?. *Sustainability*, *13*(7), 3688. https://doi.org/10.3390/su13073688.

Maysami, R. C. and Sim, H. H., 2001. An empirical investigation of the dynamic relations between macroeconomic factors and the stock markets of Malaysia and Thailand. *The Management Journal*, *20*, pp.1-20.

Pradhan, A. K., Mishra, B. R., Tiwari, A. K. and Hammoudeh, S., 2020. Macroeconomic factors and frequency domain causality between gold and silver returns in India. *Resources policy*, *68*, 101744. https://doi.org/10.1016/j.resourpol.2020.101744.

Przekota, G., Rembeza, J., Mentel, G., Szetela, B., 2019. The Relationship between the Stock Market and the Economy: Evidence from Central and Eastern European Countries. *Transformations in Business & Economics*, *18*(2A), pp.397-415.

Rajeshwaran, N., 2019. Dynamic Relationship between Macroeconomic Variables and Stock Returns: Empirical Evidence in Case of Sri Lanka, *The Journal of Business Studies*, *3*(1), pp. 35-48.

Rashid, A., Jehan, Z., Khan, M. and Saeed, M., 2019. The influence of capital flow bonanzas on real and financial sectors: a comparative study of South Asia and China. *Romanian Journal of Economic Forecasting*, *22*(4), pp.124-147.

Raza, S.A., Shahbaz, M., Amir-ud-Din, R., Sbia, R. and Shah, N., 2018. Testing for wavelet-based time-frequency relationship between oil prices and US economic activity. *Energy*, *154*, pp.571-580. https://doi.org/10.1016/j.energy.2018.02.037.

Raza, S.A., Shah, N. and Sharif, A., 2019. Time frequency relationship between energy consumption, economic growth and environmental degradation in the United States: Evidence from transportation sector. *Energy*, *173*, pp. 706-720. https://doi.org/10.1016/j.energy.2019.01.077.

Reboredo, J.C., Rivera-Castro, M.A. and Ugolini, A., 2017. Wavelet-based test of co-movement and causality between oil and renewable energy stock prices. *Energy Economics*, *61*, pp.241-252. https://doi.org/10.1016/j.eneco.2016.10.015.

Soenen, L. and Johnson, R., 2001. The interrelationship between macroeconomic variables and stock prices-the case of China. *Journal of Asia-Pacific Business*, *3*(2), pp.67-81. https://doi.org/10.1300/J098v03n02_04**.**

Tiwari, A. K., Raheem, I. D., Bozoklu, S. and Hammoudeh, S., 2022. The oil price□macroeconomic fundamentals nexus for emerging market economies: evidence from a wavelet analysis. *International Journal of Finance & Economics*, *27*(1), pp.1569-1590. https://doi.org/10.1002/ijfe.2231.

Torrence, C and PJ Webster P., J, 1999. Interdecadal changes in the ENSO–monsoon system. *Journal of Climate*, *12*(8), pp. 2679–2690. https://doi.org/10.1175/1520-0442(1999)012<2679:ICITEM>2.0.CO;2.

Torrence, C. and Compo, G. P., 1998. A practical guide to wavelet analysis. *Bulletin of the American Meteorological society*, *79*(1), 61-78. https://doi.org/10.1175/1520-0477(1998)079<0061:APGTWA>2.0.CO;2.

Wang, R., & Li, L. (2020). Dynamic relationship between the stock market and macroeconomy in China (1995–2018): new evidence from the continuous wavelet analysis. *Economic research-Ekonomska istraživanja*, *33*(1), pp. 521-539. .ttps://doi.org/10.1080/1331677X.2020.1716264.

Xiang, L., Zhang, H., Gao, K., & Xiao, Z. 2021. Oil volatility–inflation pass through in China: Evidence from wavelet analysis. *Energy Reports*, *7*, pp. 2165-2177. https://doi.org/10.1016/j.egyr.2021.04.021