

The Relationship between Monetary Growth Scissors and Chinese Stock Return

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How to cite this paper: Li, J. C., & Dong, X. Y. (2024). The Relationship between Monetary Growth Scissors and Chinese Stock Return. *Open Journal of Business and Management*, 12, 2787-2800.

<https://doi.org/10.4236/ojbm.2024.124143>

Received: June 17, 2024

Accepted: July 23, 2024

Published: July 26, 2024

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Abstract

As stock returns and Monetary Growth Scissors constitute a primary economic variable, their price fluctuations exert significant influence on the global economy and financial markets. Consequently, analyzing the co-movement and causal relationships between Monetary Growth Scissors and stock returns holds substantial practical significance. This study employs three time-varying Granger causality tests to validate the causal relationship between Monetary Growth Scissors and stock returns. We analyze the period from February 2014 to January 2024 for Monetary Growth Scissors and stock returns. Our findings are as follows: First, in this study, to investigate the causal relationship between M2-M1 and stock returns, we employed three time-varying Granger causality tests. The recursive evolution method proposed by Shi et al. (2018) demonstrated the best finite sample performance, followed by Swanson's (1998) rolling window algorithm. Second, we also found evidence of bilateral contagion effects between the M2-M1 and stock returns. Third, under the assumptions of either homoscedasticity or heteroscedasticity, from 2015 to 2024, the causal relationship persists, and the null hypothesis of no Granger causality from M2-M1 to stocks can be rejected. We also found that the time-varying Granger causality relationship from stock returns to M2-M1 was only significant from late 2015 to 2016.

Keywords

Monetary Growth Scissors, Stock Market Return, Time-varying Granger Causality, China

1. Introduction

Since October 2015, the rapid increase in demand deposits in the real sector and

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the slowdown in the growth rate of time deposits have led to a reversal in the year-on-year growth rates of M1 and M2, with a continuous upward trend. As of July 2016, this divergence has reached its historical peak at 15.2%. This rare economic phenomenon has attracted widespread attention in the academic community. The deviation in the year-on-year growth rates of M1 and M2 is commonly referred to as the “Monetary Growth Scissors”. This difference is obtained by subtracting the year-on-year growth rate of M2 from that of M1. Specifically, the year-on-year growth rate of M1 surged from 2.9% in March 2015 to 25.4% in July 2016, an astonishing increase of nearly 22.5%. Meanwhile, the growth rate of M2 remained relatively stable during this period, even experiencing a decrease of nearly 3.8% after January 2016 (The data comes from the National Bureau of Statistics of China). Normally, the trends in the year-on-year growth rates of M1 and M2 should be broadly similar. The continuous expansion of the monetary growth scissor has sparked intense debate among domestic and foreign scholars regarding its impact on asset prices.

Some scholars argue that the continued rise in M1 over the past year, along with the widening gap between the growth rates of M1 and M2, heralds an improvement in real economic momentum, which will drive asset price appreciation. However, another group of scholars believes that predicting the effect of asset price increases from the perspective of the expansion of the monetary policy scissor difference is limited. They contend that there is only a correlational relationship rather than a causal one between the monetary growth scissor and changes in asset prices.

As stock returns constitute a primary economic variable, their price fluctuations exert significant influence on the global economy and financial markets. Research indicates that the US stock market can exert profound influences on each market within the BRICS countries (Wang et al., 2017). Consequently, analyzing the co-movement and causal relationships between monetary growth scissor and stock returns holds substantial practical significance. Despite the abundant literature on the relationship between monetary growth scissor and stock returns, the economic implications of the dependence structure between monetary growth scissor and stock returns remain inconclusive.

The innovative aspects of this paper are twofold: Firstly, our long-term analysis period (January 2014 to January 2024) enabled us to investigate the evolution of the relationship between monetary growth scissor and stock returns, analyzing both their dependence and risk contagion. Secondly, our study introduced three novel methodologies. Indeed, we employed various techniques to capture the co-movement of these two variables.

While Granger causality has been employed in various studies, it is limited to testing long-term stable linear relationships. Relationships between economic variables are not necessarily long-term stable and often exhibit time-varying characteristics. This implies that causality can also be time-varying, necessitating consideration of time-varying nature when analyzing causal relationships (Maki,

2016). We conducted causal analysis using the non-parametric and non-linear Granger causality test proposed by Granger (1969) and Diks and Panchenko (2005, 2006). To discern changes in causal relationships, we employed the time-varying Granger causality test introduced by Thoma (1994), Swanson (1998), and Shi et al. (2018). The investigation into changes in causal relationships allowed us to identify the causality between monetary growth scissor and stock returns and determine its timing. Overall, our study on how monetary growth scissor co-moves with stock returns will contribute to understanding how monetary growth scissor influences stock returns.

2. Theoretical Background

Based on existing research literature, the majority of studies have focused on the correlation between monetary growth rates and asset prices, with relatively fewer studies investigating the relationship between the monetary growth scissor difference and asset prices. Hirota (2023) concluded fluctuations in stock prices are due to changes in the money supply. Monetary policy may lead to a disconnection between the stock market and the real economy. Siami-Namini (2021) also draw a conclusion that we found no evidence of a strong response pattern of commodity prices to monetary policy shocks in the short term. However, in the long term, monetary policy shocks can explain commodity prices and their components. From a policy perspective, monetary authorities should exercise caution when using monetary policy tools to influence commodity prices in the short term, as their long-term effects are inflationary without beneficial short-term impacts. Thanh et al. (2020) propose a conclusion that the evolution of stock prices during different monetary policy processes is country-dependent. Unexpected monetary shocks appear to have significant asymmetric lagged effects on stock prices, namely: 1) negative unexpected shocks have a positive impact during bull markets; 2) positive unexpected shocks have a negative impact during bear markets. Our findings suggest that monetary policymakers should consider these scenarios in future monetary supply policies to reduce the degree of uncertainty when adjusting stock prices.

Caginalp and Desantis (2011) put forward such a point of view that the non-linearity of price trends establishes an empirical and quantitative basis for underreaction and overreaction in a large dataset, facilitating an understanding of these competing motives in the market. An increase in the money supply has a significant positive impact on stock prices, while approaching recent highs has a negative impact on stock prices. Feng and Chen (2020) reported that the impact of money supply on cyclical stock prices is negative during economic upturns and positive during economic downturns. The impact of money supply on non-cyclical stock prices is positive. The effect of interest rates on cyclical stock prices depends on the proportion of the stock price bubble and is negative. The impact of interest rates on non-cyclical stock prices is positive, depending on market expectations. In the opinion of Chen et al. (2013), interest rates have a signifi-

cant negative impact on stock prices. And the money supply has little impact on stock prices. According to [Hirota et al. \(2022\)](#), controlling the money supply can help stabilize asset prices. [Ahmad and Husain \(2006\)](#) indicates that a long-term relationship between stock prices and the money supply. Further analysis reveals a unidirectional causal relationship between the money supply and the KSE 100 index in both the short and long term. This implies that the stock market is inefficient with respect to M2, and past information about monetary assets can help predict changes in stock prices. During the sample period of empirical research, there was no stable equilibrium relationship between monetary supply (M0, M1, and M2) and stock market prices. Moreover, a structural turning point in stock market prices occurred in August 2001, with equilibrium relationships observed within the two segmented intervals. [Zhang and Li \(2010\)](#) examined the correlation between monetary supply and stock prices, finding that changes in stock prices significantly influence changes in monetary supply, with different levels of monetary impact. [Li \(2011\)](#) study suggested a long-term cointegrating relationship between the money supply at various levels and stock market prices in China, where stock market prices are the cause and monetary supply is the effect.

In summary, most studies both domestically and internationally have focused on the relationship between money supply and stock market prices. However, there are structural aspects of money supply, such as the monetary growth scissor difference, which may also impact stock market prices. Yet, there is a lack of literature investigating the relationship between these factors. Against the backdrop of intense debate in academia regarding the connection between the monetary growth scissor difference and asset prices, it becomes particularly important to utilize more robust estimation methods to obtain more persuasive conclusions.

3. Data and Methodology

This article investigates the relationship between the scissors gap of money supply growth and stock prices, starting from the transmission pathway of interest rates. Firstly, it is necessary to understand what M1 and M2 scissors gaps specifically represent. The monetary supply in our country can be mainly divided into three levels, namely M0, M1, and M2. Generally, M0 refers to the circulating currency in the process of economic operation, which is currently estimated to be around 6 trillion yuan. M1 refers to the circulating currency M0 plus the demand deposits of enterprises and institutions (the demand deposits of enterprises and institutions can be paid by check, so they have the same meaning as cash). However, personal demand deposits cannot be paid by check, so they are not included. As of the end of 2015, the proportions of M0, enterprise demand deposits, and institutional demand deposits were 16%, 44%, and 40%, respectively. It is evident that the demand deposits of enterprises and institutions account for as much as 84%. In addition, the total amount of M1 has reached 17 trillion yuan. M2 refers to M1 plus quasi-money (including enterprise time de-

posits, institutional time deposits, household savings deposits, and other deposits). In other words, M2 is M1 plus all deposits in the economy, and the total amount of M2 has reached 150 trillion yuan. Despite the current economic slowdown, the continuous increase in the money supply, and the “bull market” that began at the end of 2014, have attracted attention from the economics community regarding the relationship between money supply and stock market prices.

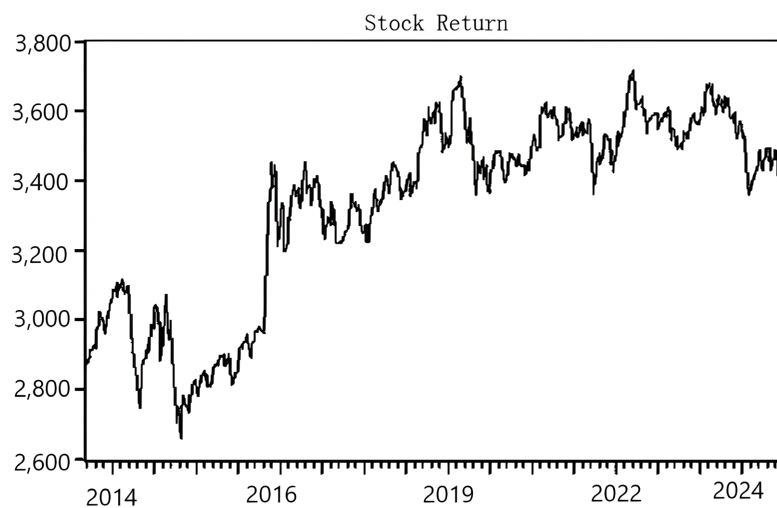
3.1. Data

The data regarding money supply in this article is sourced from the National Bureau of Statistics of China, while we employ the Shanghai Composite Index’s returns as a proxy variable for stock market returns, sourced from the Wind database. The time span for all data in the article ranges from January 2014 to January 2024, and all data are monthly. Detailed descriptive statistics for the variables are provided in **Table 1**. In the subsequent sections of the article, M2-M1 will be substituted for Monetary Growth Scissors, and RStock will replace Stock Return.

Table 1. Descriptive statistics.

Variable	Obs.	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
M2-M1	121	10.4800	1.8340	0.2469	1.8221	8.1564
RStock	121	0.0026	0.0575	-0.3390	6.8649	76.9853

Figure 1 illustrates the dynamic relationship between M2-M1 and stock returns. As depicted, the M2-M1 index experienced a downward trend from 2014 to 2015. From 2015 to 2021, it exhibited a wave-like growth pattern, followed by a sharp decline from 2021 to 2024, with a minor uptick in 2024. Regarding stock returns, there were fluctuations in 2014, followed by a rapid ascent from 2015 to 2016. Starting from 2016, they displayed fluctuations.



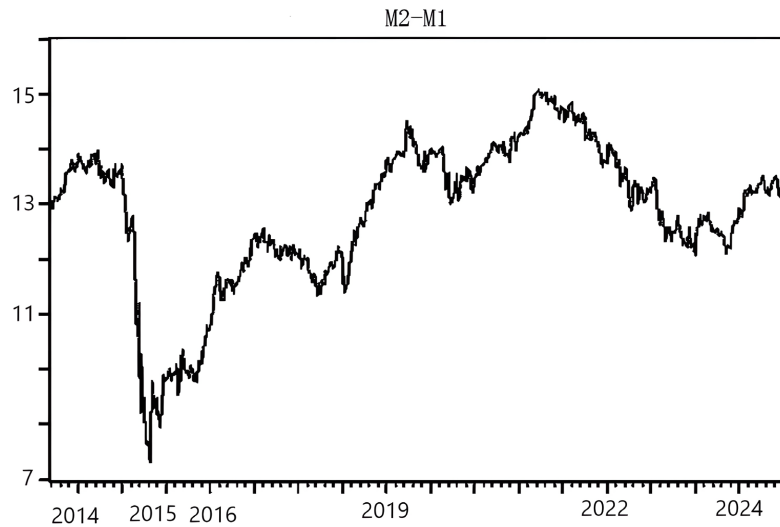


Figure 1. The dynamics of RStock and M2-M1.

3.2. Methodology

Phillips and Shi (2017)’s algorithm builds upon the recursive rolling window method introduced by Phillips et al. (2015a, 2015b), which proves to be more efficient, particularly when multiple bubbles occur within the sample period.

The PSY test can be conducted on each observed value of returns ranging from 0 to 1. It is recommended to set $r_0 = 0.01 + 1.8/\sqrt{T}$ and T as the sample length. Assuming the observed values of returns are denoted by r , the PSY sequentially calculates the Augmented Dickey-Fuller (ADF) statistic from the backward expanding sample sequences. Let r_1 and r_2 represent the starting and ending points of the regression sample, respectively. The ADF statistic computed from this sample is denoted as $ADF_n^{r_2}$. We fix the endpoints of all samples to the observed values of returns, such that $r_2 = r$, and allow the starting point r_1 to vary within the range of $[0, r - r_0]$.

In the context of the null hypothesis where $\rho = 0$, ascertain an estimation for the subsequent equation:

$$\Delta y_t = \mu + \rho y_{t-1} + \sum_{j=1}^p \Delta y_{t-j} + \gamma_t \tag{1}$$

The PSY statistic is the aggregate result obtained from all ADF statistics and is formulated as follows:

$$PSY_r(r_0) = \sup \{ ADF_n^{r_2} \}, r_1 \in [0, r - r_0], r_2 = r \tag{2}$$

Prosperity dates are considered as the first instances where the PSY test statistics exceed the critical value for the first time—this marks its initial cessation due to this event. Similarly, collapse dates are regarded as the second cessation period when the maximum test statistic eventually falls below its baseline value. Assuming only one segment in the sample originates from r_e to r_f , the estimated periods and termination dates are determined by Equation (3) and (4), as per Phillips and Shi (2017).

$$\hat{r}_e = \inf \{r : \text{PSY}_r(r_0) > cv_r(\beta_T)\}, r \in [r_0, 1] \quad (3)$$

$$\hat{r}_f = \inf \{r : \text{PSY}_r(r_0) > cv_r(\beta_T)\}, r \in [r_0, 1] \quad (4)$$

In the equation, $cv_r(\beta_T)$ represents the quantile of the $\text{PSY}_r(r_0)$ distribution from Equation (2).

3.3. Determining Changes in the Causal Relationship between M2-M1 and RStock

This paper employs three time-varying Granger causality tests proposed by Thoma (1994), Swanson (1998), and Shi et al. (2018). Thoma (1994) and Swanson (1998) advocate using forward expanding and rolling window Wald tests, respectively, to detect changes in causal relationships. In contrast, the test by Shi et al. (2018) is based on recursive rolling windows or the evolutionary process of Phillips et al. (2015a, 2015b). The specific procedure of the corrected bootstrap algorithm is as follows:

Step 1: Under the null hypothesis of no Granger causality, we estimate a VAR(1) model. The estimation process consists of two steps: firstly, estimating the relationship from y_{1t} (M2-M1) to y_{2t} (RStock), and secondly, estimating the relationship from y_{2t} (RStock) to y_{1t} (M2-M1).

Step 2: For the given dataset size, we conduct a bootstrap sample and compute the following:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \hat{\phi}_{11} & 0 \\ \hat{\phi}_{12} & \hat{\phi}_{22} \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \quad (5)$$

where ε_{1t} and ε_{2t} represent the residuals of the VAR(1) model.

Step 3: Calculate the statistical sequences for the bootstrap samples using forward, rolling, and recursive evolutionary approaches. The sequences of test statistics for each test are listed as follows:

The test proposed by Thoma (1994) is conducted using a forward procedure.

$$M_{1,t}^b = \max(W_{1,t}^b), t \in [\tau_0, \tau_0 + \tau_b - 1] \quad (6)$$

Swanson's (1998) test is conducted using a rolling procedure.

$$M_{t-\tau_0+1,t}^b = \max(W_{t-\tau_0+1,t}^b), t \in [\tau_0, \tau_0 + \tau_b - 1] \quad (7)$$

The test by Shi et al. (2018) is based on a recursive rolling window (i.e., evolutionary) process.

$$SM_t^b(\tau_0) = \max(SM_t^b(\tau_0)), t \in [\tau_0, \tau_0 + \tau_b - 1] \quad (8)$$

Step 4: Iterate Steps 2 and 3 for $B = 1$ through $B = 499$.

3.4. Correlation Analysis of M2-M1 and RStock

We estimate Pearson's linear correlation using a 30-day window. Specifically, we employ overlapping rolling windows to advance one day of observation. Figure 2 depicts the overlapping rolling window of linear correlation between Monetary

Growth Scissors and Chinese Stock Return. The correlation of changes between Monetary Growth Scissors and Chinese Stock Return fluctuates between positive and negative values. It is evident that the relationship between Monetary Growth Scissors and Chinese Stock Return undergoes significant variations over time due to bubbles and crises in both Monetary Growth Scissors and Chinese Stock Return. However, linear correlation may not adequately capture the dependency between Monetary Growth Scissors and Chinese Stock Return.

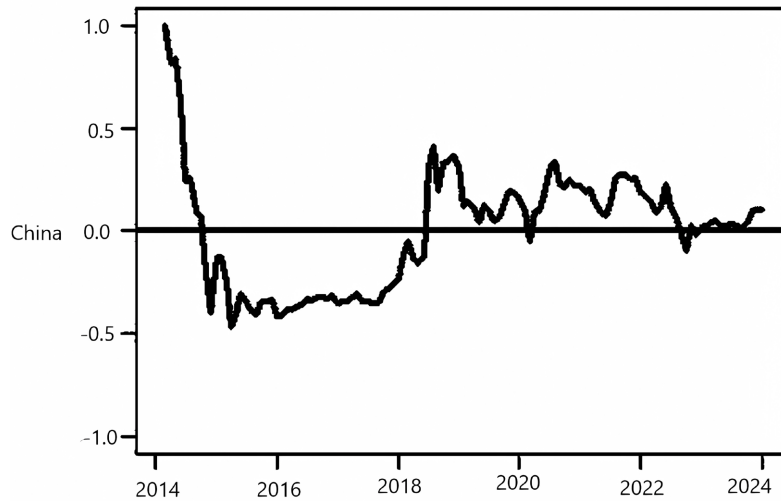


Figure 2. The Overlapping rolling correlation between M2-M1 and RStock.

3.5. Preliminary Analysis

This study conducted two Unit root tests: the augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test, to confirm the stationarity of the variables used in the data analysis. **Table 2** presents the results of the tests.

Table 2. Results of unit root tests.

	ADF	PP
M2-M1	-11.9020***	-11.8525***
stock	-8.8506***	-8.7612***

In this table, the test results indicate that the M2-M1 variable exhibits a unit root. After first differencing, both the ADF and PP tests reject the null hypothesis at the 1% significance level, rendering the M2-M1 variable a stationary series. Conversely, stock returns do not possess a unit root; at the 1% significance level, both ADF and PP tests reject the null hypothesis, indicating stationarity. Therefore, both variables are stationary series, enabling subsequent analysis.

4. Empirical Results

4.1. Testing for Crisis Identification

Figure 3 and **Table 3** report the crisis identification results of Phillips and Shi

(2017) obtained through bootstrap procedures for 95% critical values. Regarding stock returns, we identify two positive bubble-like events in July 2017, with durations of 5 days and 1 day, respectively. For M2-M1, two short bubble-like events occurred in 2015, lasting 1 day and 5 days, respectively. In 2016, one long and one short bubble-like event appeared, lasting 10 days and 4 days, respectively. In 2018 and 2020, one short bubble-like event each occurred, both lasting 1 day.

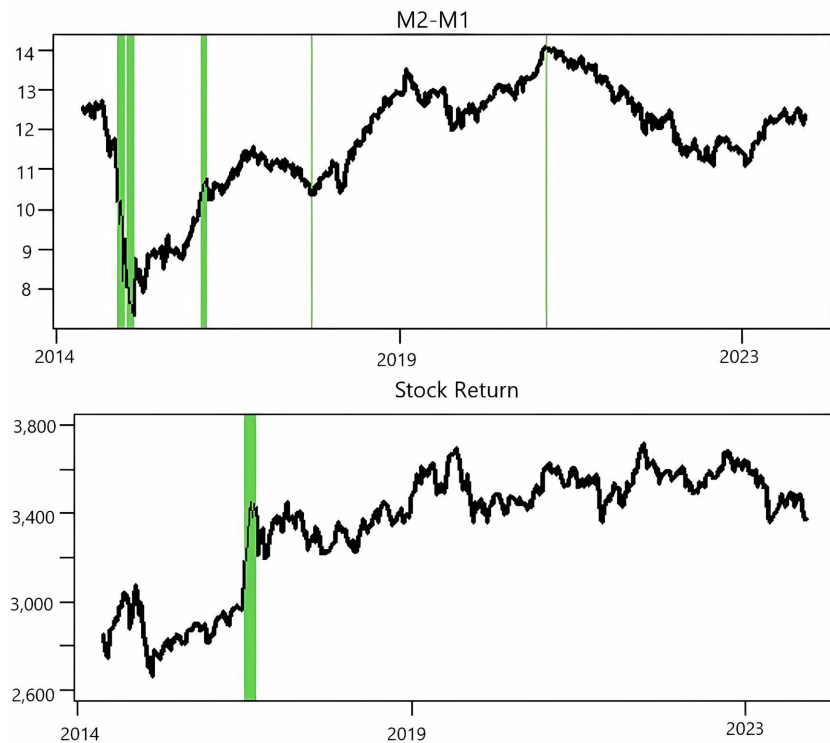


Figure 3. Bubbles and crisis in RStock and M2-M1.

Table 3. Date stamping of crises and bubbles in Stock Return and M2-M1.

Stock Exuberance date	Collapse date	Duration	M2-M1 Exuberance date	Collapse date	Duration
2017-07-05	2017-07-09	5	2015-02-27	2016-02-28	2
2017-07-13	2017-07-13	1	2015-03-06	2016-03-12	7
			2016-03-14	2016-03-23	10
			2016-06-05	2016-06-08	4
			2018-05-15	2018-05-15	1
			2020-10-05	2020-10-05	1

To conduct a comprehensive analysis of the interaction between stock returns and M2-M1, we employed causal relationship tests to assess the relationship in both directions. Specifically, we applied the linear non-Granger causality test and the nonparametric-nonlinear version of the Granger non-causality test proposed by [Diks and Panchenko \(2005, 2006\)](#).

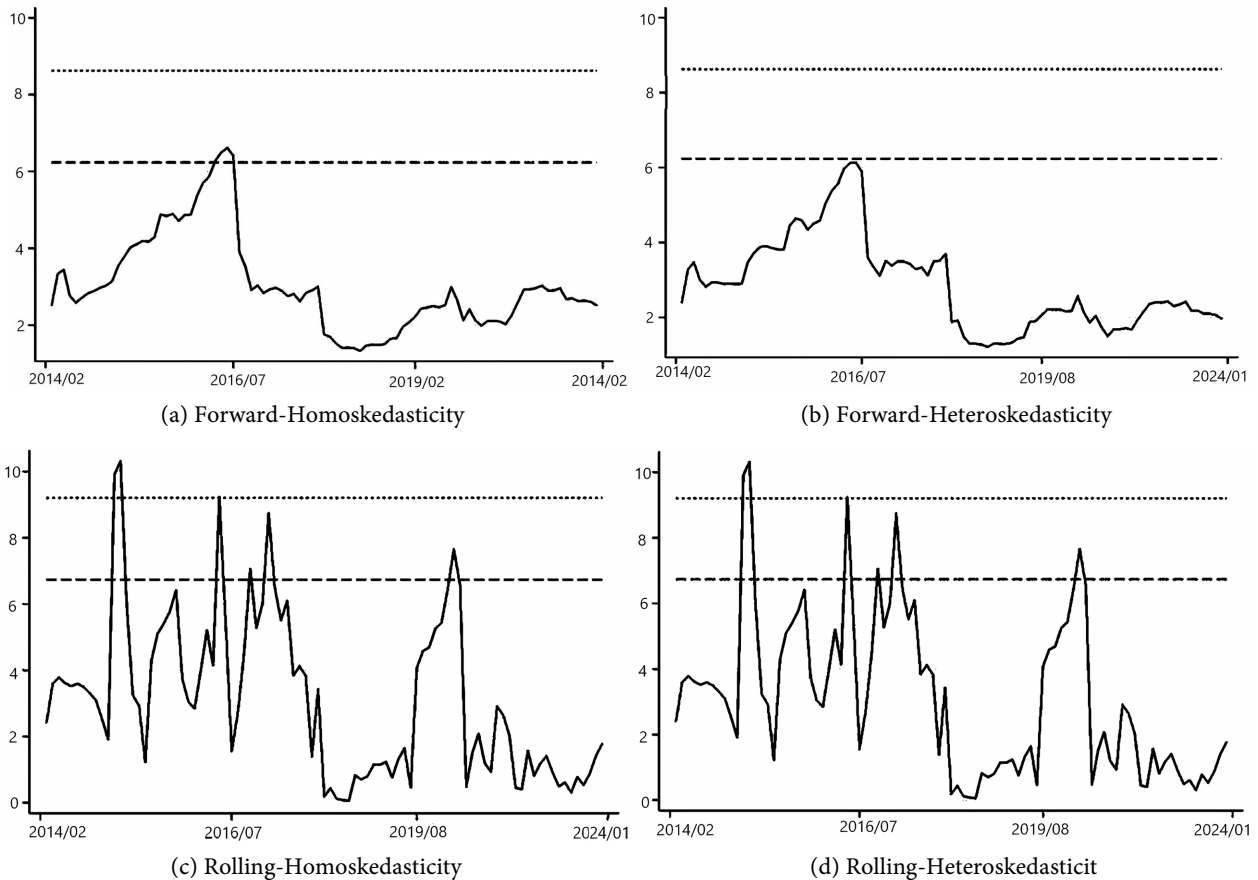
As shown in **Table 4**, the results indicate the absence of bidirectional causality between stock returns and M2-M1. Furthermore, we observe that both the non-linear causality relationships and linear causality relationships fail to reject the null hypothesis, indicating no Granger causality between the two variables. Importantly, this interpretation of causality may be attributed to the time-varying behavior of dynamic correlations and the presence of explosive processes or bubbles in these markets.

Table 4. Linear and non-linear Granger causality.

	Linear test	Non-linear test
M2-M1 running to Stock	0.9845	-1.9927
Stock running to M2-M1	2.1151	-0.3884

4.2. Detecting Variations in Causal Relationships

For the time-varying Granger causality test, the minimum window size is set at $f_0 = 0.2$, encompassing 121 observations. The critical values are obtained from 499 bootstrap iterations. The empirical scope is at a significance level of 5%, with a control period spanning three years. Following [Shi et al. \(2018\)](#), three time-varying Granger causality tests are conducted under the assumption of heteroskedasticity in VAR residuals.



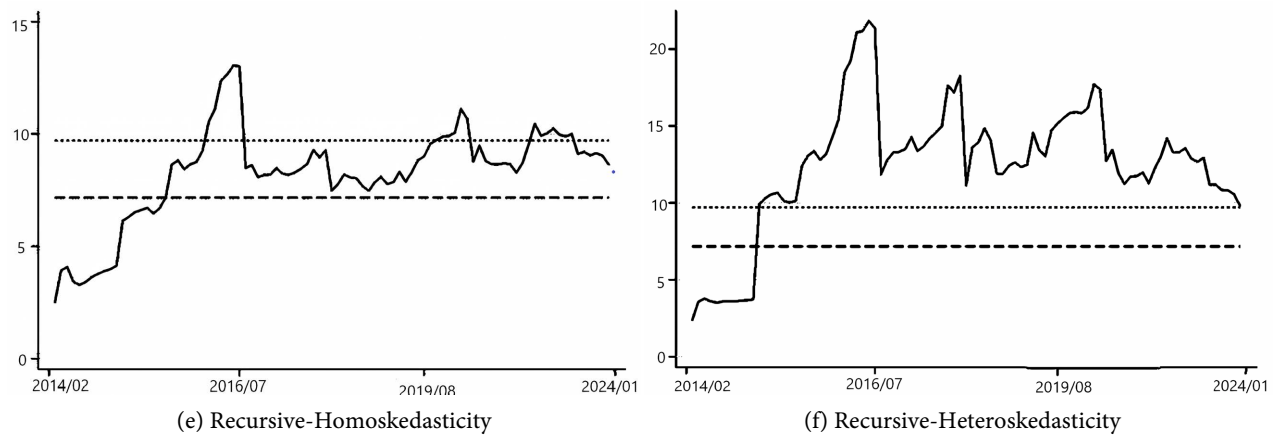


Figure 4. The Granger causality test from M2-M1 to Stock.

Note: The Granger causality test from daily M2-M1 to Stock returns is conducted from February 2014 to January 2024. The solid line represents the test statistic sequence. The dashed lines below indicate the 5% critical value sequence, while those above indicate the 10% critical value sequence. The first, second, and third rows correspond to the test statistic sequences obtained from [Thoma \(1994\)](#)'s rolling window test, [Swanson \(1998\)](#)'s rolling window test, and [Shi et al. \(2018\)](#)'s recursive evolutionary test, respectively. The columns in [Figure 4](#) and [Figure 5](#) represent the homoskedastic and heteroskedastic assumptions of the VAR(1) model residuals.

Panels (a) and (b) of [Figure 4](#) indicate that throughout the entire sample period, the test statistics for the forward causality test by [Thoma \(1994\)](#) are consistently lower than the critical values. Hence, the null hypothesis of no Granger causality between M2-M1 and Stock cannot be rejected over the entire sample period.

Under the homoskedasticity assumption, according to [Swanson's \(1998\)](#) rolling test (Panel (c) of [Figure 4](#)), we find evidence of a causal relationship from M2-M1 to Stock during the period of 2017. Conversely, under the heteroskedasticity assumption (Panel (d) of [Figure 4](#)), we identify multiple causal relationship periods from M2-M1 to Stock: in 2015, 2016, 2017, and 2019. This underscores the risk of overlooking homoskedasticity/heteroskedasticity in financial time series analysis.

Under the homoskedasticity assumption, utilizing the consistent recursive evolutionary algorithm by [Shi et al. \(2018\)](#) (Panel (e) of [Figure 4](#)), a causal relationship persists from 2015 to 2024. In contrast, the heteroskedasticity consistent recursive evolutionary algorithm (Panel (f) of [Figure 4](#)) yields results similar to those of homoskedasticity; hence, the null hypothesis of no Granger causality between M2-M1 and Stock can be rejected after 2015.

[Figure 5](#) displays the time-varying Wald test statistics for the causal effect from Stock to M2-M1. Throughout the entire sample period, the results align with the forward causality test statistics by [Thoma \(1994\)](#) in [Figure 5](#). Hence,

the null hypothesis of no Granger causality between M2-M1 and Stock cannot be rejected over the entire sample period.

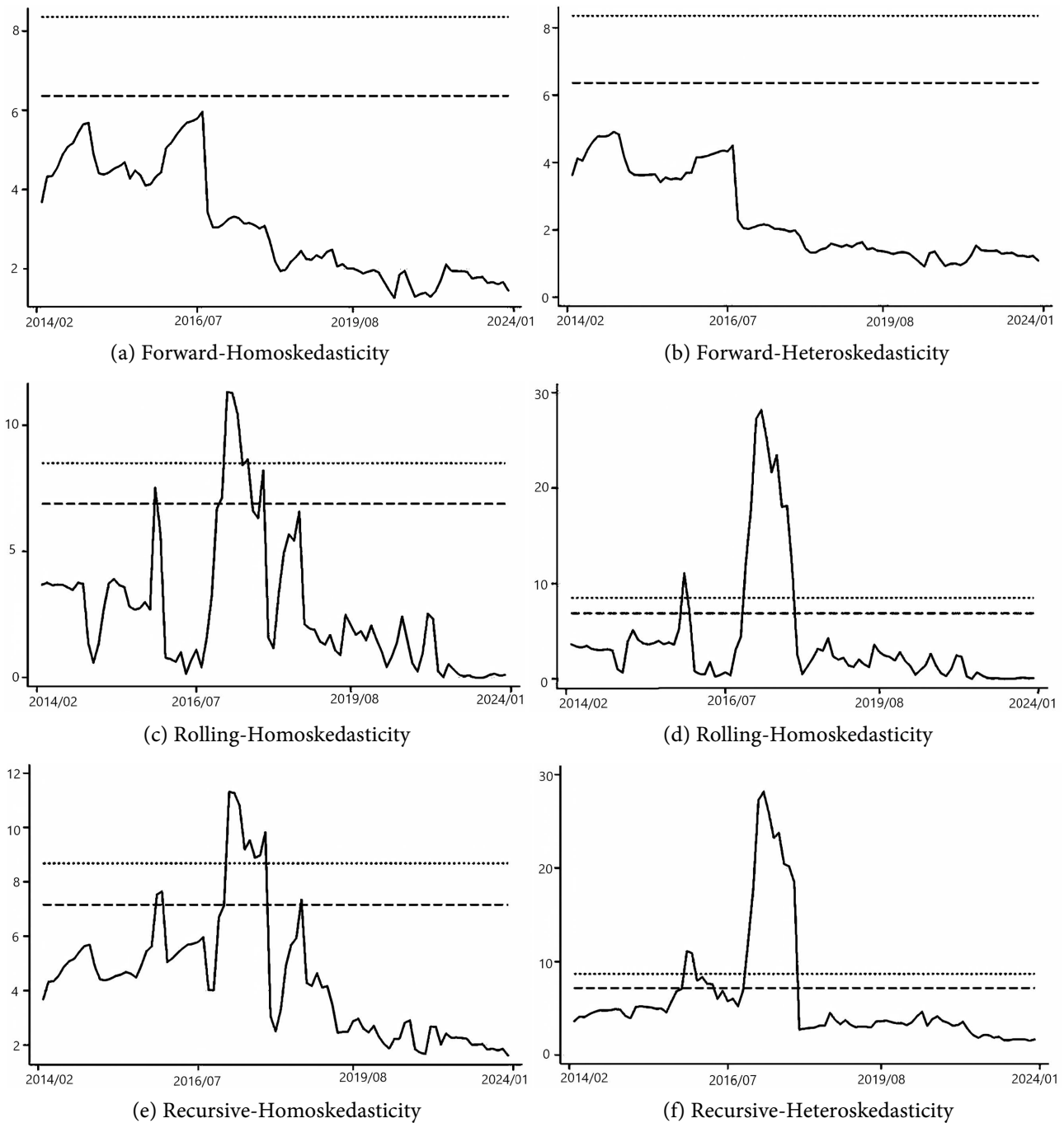


Figure 5. The Granger causality test from Stock to M2-M1.

By applying Swanson's (1998) rolling test under the homoskedasticity assumption (Panel (c) of Figure 5), we also detect three short causal events in 2016 and 2017. In contrast, under the heteroskedasticity assumption (Panel (d) of Figure 5), we similarly identify two short causal events in 2016 and 2017.

Under the homoskedasticity assumption and utilizing the consistent recursive evolutionary algorithm by Shi et al. (2018) (Panel (e) of Figure 3), we identify three short causal events from Stock to M2-M1 during 2016, 2017, and 2018. In contrast, under the heteroskedasticity assumption (Panel (f) of Figure 5), we find two longer causal events in 2016 and 2017. Our findings are consistent with those of Shi et al. (2018). The recursive evolutionary method proposed by Shi et al. (2018) demonstrates the best finite sample performance, followed by Swanson's (1998) rolling window algorithm.

5. Conclusion

Our conclusions are as follows: First, in this study, to investigate the causal relationship between M2-M1 and stock returns, we employed three time-varying Granger causality tests. The recursive evolution method proposed by Shi et al. (2018) demonstrated the best finite sample performance, followed by Swanson's (1998) rolling window algorithm. Second, we also found evidence of bilateral contagion effects between the M2-M1 and stock returns. Third, under the assumptions of either homoscedasticity or heteroscedasticity, from 2015 to 2024, the causal relationship persists, and the null hypothesis of no Granger causality between M2-M1 and stocks can be rejected.

Our findings bear practical significance as they provide guidance for policy-makers tasked with making decisions regarding financial stability measures. Indeed, given the interconnections between stock prices and overall economic activities, including other commodity prices, identifying causal relationships is of paramount importance. They are also applicable to various market participants (price change forecasting, portfolio diversification, cross hedging, and cross speculation).

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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