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Stock Market Interactions between the BRICS and the United States: Evidence from Asymmetric Granger Causality Tests in the Frequency Domain

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Abstract

The interaction of BRICS stock markets with the United States is studied using an asymmetric Granger causality test based on the frequency domain. This type of analysis allows for both positive and negative shocks over different horizons. There is a clear bivariate causality that runs both ways between the United States stock market and the respective BRICS markets. In addition, both negative and positive shocks in the United States stock market affect the majority of BRICS markets.

Keywords: Granger-Causality, Asymmetry, Frequency Domain, Stock Market, BRICS Countries.
JEL Classification: C1, G15.

1. Introduction

A survey of the transmission of stock market shocks between BRICS countries and the United States (US) suggests that there exists a close relationship between these markets and that diversification gains have dissipated over time (see Morales, 2011; Bekiros, 2013). We use a novel approach to study stock market interactions by using an asymmetric Granger causality test with a specific focus on the frequency domain (unlike most studies that focus on the time domain). We are able to study both negative and positive shocks over business cycles. Our results differ from previous studies. We show that that causality can run both ways - from the US to BRICS and BRICS to

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the US and this is dependent on the type of shock (negative or positive), which affects the duration over different business cycle frequencies. The benefit of using the frequency domain lies in the ability to identify the *strength* and *direction* of Granger causality over different frequencies.

Most studies that analyze stock market interactions rely on methods in the time domain.[1] Chang and Chu (2014) show that traditional approaches to Granger causality (GC, hereafter) yield many interesting insights, but they generally underscore the possibility that the strength and/or direction of the Granger Causality relationship, if any, could vary over different frequencies. Decomposing GC into various frequencies was already proposed by Granger (1969). Spectral-densities provide a holistic picture in comparison to a single output that applies across all periodicities (e.g., in the short run, over the business cycle frequencies, and in the long run). Apart from analyzing GC tests across different frequencies we also analyses the asymmetric shocks. This gives us two specific contributions to the literature. Our data covers many interesting financial episodes such as the 2008/09 financial crises, periods of excessive growth in commodities (such as in 2008 regarding oil, gold and platinum prices), and periods of recovery - just after the dot-com crises in the US in 2000 and just after the 2008 financial crises. The proposed GC test offers an intuitive way to analyze these episodes. We can decompose shocks emanating from the US and analyze how it affects BRICS markets, and vice versa.

The BRICS countries represent an interesting group for analysis. Apart from its trade linkages to the rest of the world, financial development has been impressive. They have experienced strong growth in GDP terms and some analyst forecast that if current growth rates can be sustained it will overtake G6 countries in U.S. dollar terms.[2] The BRICS countries are already playing important roles in global financial development, exerting significant influences on economic growth throughout the global economy and markets.

1. For an excellent survey regarding the stock market transmissions between the US and the BRICS countries, interested readers are referred to Zhong et al. (2014).
2. Brazil, Russia, India, and China constituted the BRIC group; South Africa was added later. G6 refers to the United States, the United Kingdom, Japan, Germany, France, and Italy.

A number of recent studies show that the BRICS stock markets and the US stock market are very interlinked using a combination of both linear and nonlinear cointegration and GC tests. Bekiros (2013) examines the linear and nonlinear causal linkages that uncover the nature of volatility spill-overs from the US, EU and BRIC countries. Bekiros shows that the BRIC countries have become more integrated internationally since the US financial crisis - no decoupling evidence. They use the Baek and Brock (1992) test to identify nonlinear causality. Bekiros also shows that nonlinear causality can be explained by volatility effects by filtering the Baek-Brock residuals in a nonlinear GARCH model.

Sheu and Liao (2011) show that there exists both time-varying cointegration and time-varying Granger-causality between the US stock market (paying particular attention on the Dow Jones Index) and the BRIC stock markets. They use rolling and recursive windows of the Enders and Siklos (2001) threshold cointegration test. They also show that this interaction has strengthened since the 2008 financial crises and suggest that diversification gains consequently diminished. Further evidence by Zhong et al. (2014) show that there is a strong indication of cointegration between the BRICS countries and the US using nonparametric cointegration.

The use of an asymmetric GC test, and in particular the Hatemi-J (2012) test, has been applied in a paper analysing the linkages between Islamic stock markets and the US Dow Jones Index (Ajmi et al., 2014). Hatemi-J (2012) uncovers interesting negative and positive causal relationships among the stock markets. The author finds that bad news have a stronger impact on causality. One motivation for using an asymmetric GC test is that investment strategies differ over time-horizons. Investors diversify portfolios over the short, medium and long-term using a variety of input measures to make decisions. Because of this, the economic interpretation of symmetric Granger causality tests over a fixed sample should be interpreted with caution. Consequently, this study contributes to the literature by analysing asymmetric Granger causality over different horizons by extending the asymmetric causality test to the frequency domain.

The rest of the paper is organized as follows. Section II discusses aspects of the data. Section III sets out the technical details of the methodology. The results are presented in Section IV and Section V concludes the paper.

2. Data

We use weekly stock market indices for the US and the BRICS countries. The stock market indices for the BRICS countries are the BOVESPA Index for Brazil, the RTS Index-Price Index for Russia, the BSE (100) for India, both Shanghai and Shenzhen Composite Indices for China, and the FTSE/JSE Index for South Africa. For the US, both the Dow Jones industrial Average Index and S&P stock price Index are used. The sample period covers July 1997 to March 2012. Data are obtained from the DataStream database. All indices are based on local currencies and all series are measured in logs. Following Chowdhury (1994), we match the 8 time series by omitting some observations. For example, seasonal festival or holiday entries (and others) are omitted to guarantee that each pair of countries have entries on a given date. According to Chowdhury (1994), this procedure solves the problem of the data gap caused by holidays and other nonworking days.

Table 1 reports the summary statistics of stock market weekly returns for the United States and BRICS countries. We find that most of the weekly index returns are positive, and that Russia and the United States (S&P 500) have the highest and lowest average weekly index returns of 0.3866% and 0.0558%, respectively. Table 1 also shows that index returns for all countries are leptokurtic. The relatively large value of the kurtosis statistic (larger than three) suggests that the underlying data is heavily tailed and sharply peaked about the mean when compared to the normal distribution - implying that there is possibly volatility clustering and fat tails. Consequently, the Jarque-Bera test rejects normality for the eight equity returns series.

The presence of volatility clustering is detected by using a multivariate normality test and multivariate ARCH (autoregressive conditional heteroskedastisity) . The results are presented in panel A of Table 3. The results for actual SPI series, positive and negative shocks indicate the residuals are not normally distributed. Also the null hypothesis of no multivariate ARCH(1) is rejected only for causality between positive shocks of S&P and SPI series of Brazil, India, Russia, Shangha and South Africa. The results indicate that time-varying volatility prevails. This motivates the use of the bootstrap simulation method to adjust for heteroskedasticity.

Anecdotal evidence suggests that the Chinese markets are least correlated with the US, followed by Indian and Russian Markets (see Figure 1). The Brazilian and South African stock markets seem to have the highest correlation with the US.

3. Asymmetric Granger Causality Test in Frequency Domain

The Hatemi-J (2012) test allows for asymmetric causal effects. Positive or negative shocks may have different causal impacts. Assume that two integrated variables $\{y_t\}_{t=1}^{T}$ and $\{x_t\}_{t=1}^{T}$ has the following data generating process (DGP):

$$y_t = y_{t-1} + \varepsilon_{1t} = y_{10} + \sum_{i=1}^{T} \varepsilon_{1i} \tag{1}$$

and

$$x_t = x_{t-1} + \varepsilon_{2t} = x_{10} + \sum_{i=1}^{T} \varepsilon_{2i} \tag{2}$$

Where y_{10} and x_{10} are the initial values of y and x respectively, and the variables ε_{1t} and ε_{2t} are i.i.d with variance $\sigma_{\varepsilon_1}^2$ and $\sigma_{\varepsilon_2}^2$ respectively. Positive and negative shocks are defined as the following: $\varepsilon_{1t}^{+} = \max(\varepsilon_{1t},0), \varepsilon_{2t}^{+} = \max(\varepsilon_{2t},0), \varepsilon_{1t}^{-} = \min(\varepsilon_{1t},0), \text{and}\ \varepsilon_{2t}^{-} = \min(\varepsilon_{2t},0)$ respectively. Therefore, we can express $\varepsilon_{1t} = \varepsilon_{1t}^{+} + \varepsilon_{1t}^{-}$ and $\varepsilon_{2t} = \varepsilon_{2t}^{+} + \varepsilon_{2t}^{-}$ and write equations (1) and (2) as:

$$y_t = y_{t-1} + \varepsilon_{1t} = y_{10} + \sum_{i=1}^{t} \varepsilon_{1i}^{+} + \sum_{i=1}^{t} \varepsilon_{1i}^{-} \tag{3}$$

and

$$x_t = x_{t-1} + \varepsilon_{2t} = x_{10} + \sum_{i=1}^{t} \varepsilon_{2i}^{+} + \sum_{i=1}^{t} \varepsilon_{2i}^{-} \tag{4}$$

Following Granger and Yoon (2002), Hatemi-J (2012) defines positive and negative shocks of each variable in a cumulative form such that $y_t^{+} = \sum_{i=1}^{t} \varepsilon_{1i}^{+}$, $y_t^{-} = \sum_{i=1}^{t} \varepsilon_{1i}^{-}$, $x_t^{+} = \sum_{i=1}^{t} \varepsilon_{2i}^{+}$, and $x_t^{-} = \sum_{i=1}^{t} \varepsilon_{2i}^{-}$. Each positive as well as negative shock has a permanent impact on the underlying variable. To test the causal relationship between these two components, Hatemi-J (2012) developed a single test statistic in time domain, assuming it holds for all points in the frequency distribution. Our extension follows a suggestion by Granger (1969 and 1988) that the strength and/or direction of the Granger causality vary over different frequencies. Granger (1969) suggests that using spectral densities would solve this problem. We follow this approach by extending the Hatemi-J (2012) asymmetric causality test in the frequency domain based on Breitung and Candelon (2006). Despite having four combinations of positive and negative shocks $((y_t^+, x_t^+), (y_t^+, x_t^-), (y_t^-, x_t^+), \text{and } (y_t^-, x_t^-))$ we simplify it to only two combinations (y_t^+, x_t^+) and (y_t^-, x_t^-) as suggested by Hatemi-J (2012). To illustrate our causality measure, consider the following bivariate finite-order VAR model:

$$\theta_{12} = [\theta_{12,1}, \theta_{12,2}, ..., \theta_{12,p}]'$$

Where $\Theta(L) = I - \sum_{i=1}^{p} \theta_i L^i$ is autoregressive polynomials with $L^k y_t^+ = y_{t-k}^+$. We assume that the error vector $\vartheta_t = (\vartheta_{1t}, \vartheta_{2t})'$ is multivariate-normal with $E(\vartheta_t) = 0$ and $E(\vartheta_t \vartheta_t') = \Sigma$, where Σ is positive definite and symmetric. Using this definition for Σ, a Cholesky decomposition $GG' = \Sigma^{-1}$ exists, where G and G' are lower and upper triangular matrices. The moving average (MA) representation of the stationary system is then:

$$\begin{pmatrix} y_t^+ \\ x_t^+ \end{pmatrix} = \begin{pmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{pmatrix} \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \end{pmatrix} \tag{6}$$

Where the vector $\eta_t = (\eta_{1t}, \eta_{2t})'$, $\eta_t = G\vartheta_t$, $E(\eta_t \eta_t') = I$, and $\Psi(L) = \Theta(L)^{-1} G^{-1}$. Using these definitions, we can express the spectral density of y_t^+ as:

$$f_{y^+}(\omega) = \frac{1}{2\pi} \left\{ |\psi_{11}(e^{-i\omega})|^2 + |\psi_{12}(e^{-i\omega})|^2 \right\} \tag{7}$$

The measure of causality in the frequency domain suggested by

Geweke (1982) is defined as:

$$M_{x_t^+ \to y_t^+}(\omega) = \log\left[\frac{2\pi f_{EX}(\omega)}{|\psi_{11}(e^{-i\omega})|^2}\right] = \log\left[1 + \frac{|\psi_{12}(e^{-i\omega})|^2}{|\psi_{11}(e^{-i\omega})|^2}\right] \quad (8)$$

Testing the null hypothesis of no Granger causality from x_t^+ to y_t^+ is equivalent to $M_{x_t^+ \to y_t^+}(\omega) = 0$ i.e. $|\psi_{12}(e^{-i\omega})| = 0$ in equation (8). Where $\psi_{12}(L) = -\frac{g^{22}\Theta_{12}(L)}{|\Theta(L)|}$ with g^{22} as the lower diagonal element of G^{-1} and $|\Theta(L)|$ is the determinant of $\Theta(L)$. Σ is positive definite, g^{22} is positive valued and thus $|\psi_{12}(e^{-i\omega})| = 0$ if

$$|\Theta_{12}(L)(e^{-i\omega})| = \left|\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega) - \sum_{k=1}^{p}\theta_{12,k}\sin(k\omega)i\right| = 0 \quad (9)$$

Where $\theta_{12,k}$ is the (1,2)-element of Θ_k. The necessary and sufficient conditions for (9) are as follows:

$$\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega) = 0 \quad (10)$$

$$\sum_{k=1}^{p}\theta_{12,k}\sin(k\omega) = 0 \quad (11)$$

Following to Breitung and Candelon (2006), we specify a VAR(p) equation for y_t^+[1]:

$$y_t^+ = \sum_{k=1}^{p}\theta_{11,k}y_{t-k}^+ + \sum_{k=1}^{p}\theta_{12,k}x_{t-k}^+ + \varpi_t \quad (12)$$

A necessary and sufficient condition for no Granger causality $M_{x_t^+ \to y_t^+}(\omega) = 0$ at frequency ω is given by:

$$H_0 = R(\omega)\theta_{12} = 0 \quad (13)$$

Where $\theta_{12} = [\theta_{12,1}, \theta_{12,2}, ..., \theta_{12,p}]'$ and $R(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & ... & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & ... & \sin(p\omega) \end{bmatrix}$

1. We select the optimum lag order p in the VAR model (12) which minimize the following information criterion suggested by Hatemi-J (2008):

$$HJC = \ln(|\hat{\Omega}_p^+|) + p(2T)^{-1}(m^2\ln(T) + 2m^2\ln(\ln(T))), \qquad p = 1,2,...,l_{max} \qquad (12-1)$$

where $\hat{\Omega}_p^+$ is the determinant of the estimated variance–covariance matrix of the error term in the VAR model (12) using lag order p, m is the number of variables and T is the sample size.

The linear restrictions of equation (13) can be tested by an ordinary Wald statistic. The ordinary Wald statistic for (13) follows a χ^2-distribution with 2 degree of freedom, where 2 is the number of restriction for $\omega \in (0, \pi)$. But, as noted by Hatemi-J(2012), due to the existence of autoregressive conditional heteroskedasticity (ARCH) effects in financial data, they do not usually follow a normal distribution and hence there is the possibility that the distribution of the Wald statistic substantially deviates from its asymptotic distribution. We thus use the bootstrapping simulation technique based on Hatemi-J (2012): Step 1, estimate (12) while imposing the null hypothesis of Granger non-causality and then save the residuals ($\hat{\varpi}_{it}$) and the fitted $\hat{y}_t^+$. Step 2, generate bootstrap residuals $\tilde{e}_t$ sampling with replacement of t values from the residual matrix. To ensure that pseudo residual series are mean zero and constant variance, we subtract the mean value of the pseudo residual series from each of the modified residuals in that particular set and then adjust via leverages. Step 3, calculate the bootstrap sample of observations $\tilde{y}_t^+$ as $\tilde{y}_t^+ = \hat{y}_t^+ + \tilde{e}_t$. Step 4, construct the pseudo Wald statistics for $\omega \in (0, \pi)$. Finally, in step 5, we repeat steps 1-4 for 5000 iterations to construct the 10%, 5%, and 1% critical values for $\omega \in (0, \pi)$ from the empirical distribution.

As noted by Breitung and Candelon (2006), to test the causality in the cointegrated system, y_t^+ in equation (12) should be replaced with Δy_t^+, while the right-hand side of the equation remains the same. For the case when one variable is I(1) and other is I(0), the VAR model can be augmented with a redundant unrestricted lag in order to take into account the effect of one unit root as suggested by Toda and Yamamoto (1995).

4. An Application for Interactions between U.S. Stock Markets and BRICS Countries[1]

Table 2 reports the results of ADF unit root test for actual SPI series and also positive and negative shocks of SPI series in panels A, B and

1. The results for both the Dow Jones industrial Average Index and S&P stock price Index are same in most cases. In order to save the space, we report the results for S&P stock price index.

C respectively. The null hypothesis of a unit root is only rejected for Brazil on both positive and negative shock in levels. However, none of the unit root tests are rejected when we allow for both an intercept and trend.[1] In contrast, the null hypothesis of a unit root can be rejected for both cases (model with intercept and model with intercept and trend) when using first differences. It is thus assumed that all SPI series are I(1). Next we test for the existence of any long-run cointegrated relationship between actual SPI series and also the negative and positive shocks of the SPI for both the U.S. and BRICS countries. We use the Engle-Granger (1987) bivariate cointegration test. In contrast to Zhong et al. (2014), the Engle-Granger cointegration test results indicate that the null hypothesis of no cointegration can not be rejected for both the negative and positive shocks of the U.S. and the BRICS countries at 5% level of significance.[2] Since all actual SPI series and also positive and negative shocks of SPI series are I(1) and not cointegrated, we follow Toda and Yamamoto(1995) and Hatemi-J(2012) and include an additional unrestricted lag in our testing model.

As a benchmark, we analyze both symmetric and asymmetric GC in time domain, and then compare the GC tests in the frequency domain. Panel B of Table 3 reports the symmetric and asymmetric Granger causality test in time domain from the US stock market to those of the BRICS countries. Table 4 reports both symmetric and asymmetric Granger causality in time domain from the stock markets of the BRICS countries to the US stock market. The results from panel B of Table 3 show that the null hypothesis of no causality is rejected for all the countries except for South Africa using the symmetric Granger causality specification. This implies that the US stock market Granger causes all the stock market of the BRICS countries, with the exception of South Africa. Table 4 shows that only the Shenzhen market of China Granger causes the US stock market. In terms of asymmetric Granger causality test in time domain, both Table 3 and Table 4 shows that a negative shock emanating from the US market affects the Russian market. A negative shock coming from

1. This result is supported by other unit root tests including the Phillips and Perron (1988), Kwiatkowski et al. (1992), and Andrews and Zivot (1992) break test. The results are available if requested.
2. The results not presented in order to save space, but available if requested.

both the Brazilian and Indian markets affects the US. These results are fairly consistent with the previous studies mentioned and shows that news in US markets are transmitted to BRICS countries. However, the converse does not necessarily hold - news in BRICS markets seem to have no to little causal impact on the US.

Next, we extend the analysis to uncover period specific causality in the frequency domain. Figure 2 shows the symmetric Granger causality from U.S Stock Market to the BRICS Stock Markets in the frequency domain. The results indicate the US stock market affects the markets in Russia, India, Shanghai and South Africa in all possible periods - short, medium and long-run. It affects the ShenZhen market in medium and short-run periods and Brazil only in the medium-term.

In contrast, symmetric Granger causality from the BRICS Stock Markets to U.S Stock Market in the frequency domain indicate that only the South African market (in medium and short-run), Brazilian market (short-run) and Russian market (in medium and short-run) affect the US market (see Figure 3).

Figures 4 and 5 show the asymmetric GC from the US market to the BRICS markets. The effects of positive and negative shocks clearly vary over different frequencies. A positive shock from the US market affects the Brazilian market in both low and medium frequencies (medium and long – term periods), while a negative shock from the US market affects the Brazilian market in both high and medium frequencies (short and medium-term).

A positive shock from the US market affects Russia's market in both medium and high frequencies (medium and short-term), and a negative shock from the US market affects Russia's market in all frequencies (short, medium and long-term). A positive shock from the US market does not have any effect on India's market while a negative shock from the US market affects India market in medium and high frequencies (medium and short-term). The results for China's two markets (Shanghai and Shenzhen) are similar: a positive shock from the US market affects both markets in high and medium frequencies (short and medium – term), and a negative shock from the US affects both markets in medium and high frequencies (medium and short-term). A positive shock from the US market does not have any effect on South Africa's market while a negative shock from the US market affects South Africa t in medium frequencies (medium -term).

Figures 6 and 7 show the asymmetric GC from the BRICS markets to the US market. Only positive shocks from the South Africa market affects the US market in the medium –term, while positive shocks of other BRICA market do not have any effect on the US market. The results of asymmetric GC from negative shocks of the BRICS markets to the US market in Figure 7 show they do not have any effect on the US market.

These asymmetric frequency effects are summarized in Figure 8 (only shocks from the US to BRICS). Negative shocks affect all the BRICS countries in the medium-term. Except for South Africa, US shocks have short-term causal effects in all the BRICS countries. There seems to be no long-term causality from negative shocks. Positive shocks from the US to BRICS show no causality in the short-term expect for Russia. There seems to be no GC from positive US shocks to India and South Africa at any frequency, which in contrast to the symmetric GC test.

5. Conclusion

We study the stock market interactions between the US and BRICS countries using an asymmetric Granger causality test based on the Frequency domain. We show that asymmetry matters and that the effects of positive and negative shocks differ across the duration of economic cycles. Granger causality in the time domain shows that US shocks has an impact on all BRICS countries except for South Africa. The asymmetric Granger causality tests in the frequency domain shows that some shocks are more prevalent in specific periods. Negative or positive shocks also matter - not all shocks emanating from the US Granger-causes every country. Our results also show that some of the shocks in the BRICS countries affect the US. However, it is conditional on the type of shock.

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Appendices:

Table 1: **Summary Statistic (Stock Market Return)**

Country	S&P500	Brazil	Russia	India	Shanghai	ShenZhen	South Africa
Mean	-0.008858	-0.012351	-0.007489	-0.009773	-0.009163	-0.007808	-0.011432
Median	0.001584	0.005569	0.004758	0.007036	0.000000	0.000000	0.003378
Maximum	0.113559	0.217421	0.544976	0.152186	0.139447	0.154317	0.160396
Minimum	-7.250259	-11.07459	-8.739420	-9.123045	-7.724353	-6.793290	-10.42092
Std. Dev.	0.262699	0.401894	0.322000	0.331067	0.280473	0.247811	0.376856
Skewness	-27.25475	-27.13568	-25.95643	-27.14052	-27.08289	-26.71190	-27.42270
Kurtosis	751.7881	747.4199	704.1842	747.6046	745.5264	731.9503	757.9765
Jarque-Bera	18083931	17873828	15860531	17882689	17783132	17139643	18383673

Table 2: ADF Unit Root Test Results

Panel A: The results for actual series (in log form)

Series	Level		First difference	
	Intercept	Intercept & Trend	Intercept	Intercept & Trend
S&P	-2.489	-2.485	-29.984***	-29.965***
Brazil	-0.627	-2.878	-18.212***	-18.199***
Russia	-1.610	-1.606	-25.881***	-25.893***
India	-0.716	-2.442	-16.598***	-16.59***
ShenZhen	-0.997	-1.510	-25.744***	-25.726***
Shangha	-1.466	-1.448	-26.072***	-26.065***
South Africa	-0.477	-2.575	-27.827***	-27.811***

Panel B: The results for positive shock

Series	Level		First difference	
	Intercept	Intercept & Trend	Intercept	Intercept & Trend
S&P	-0.091	-1.081	-30.174***	-30.154***
Brazil	-3.722***	-1.809	-31.029***	-31.479***
Russia	-2.068	-2.889	-13.045***	-13.177***
India	-0.979	-1.271	-25.66***	-25.672***
ShenZhen	1.766	-0.9	-12.652***	-12.825***
Shangha	1.205	-0.986	-25.974***	-26.025***
South Africa	-0.859	-1.832	-28.175***	-28.179***

Panel C: The results for negative shock

Series	Level		First difference	
	Intercept	Intercept & Trend	Intercept	Intercept & Trend
S&P	-0.048	-1.174	-15.838***	-15.828***
Brazil	-2.785*	-2.959	-13.038***	-16.418***
Russia	-1.125	-2.124	-16.224***	-16.237***
India	-1.299	-1.714	-15.151***	-15.193***
ShenZhen	2.519	-0.508	-25.168***	-25.355***
Shangha	2.305	-0.904	-25.339***	-25.502***
South Afica	-1.193	-1.869	-16.242***	-16.273***

Note: * and *** indicate significance at the 10% and 1% level, respectively.

Table 3: Symmetric and Asymmetric Granger Causality in Time Domain – from the US Market to the BRICS Markets

Panel A: Multivariate diagnostic tests for normality and ARCH

Variables in the VAR model	Actual series (in log form)		Positive shocks		Negative shocks	
	Multivariate normality	Multivariate ARCH	Multivariate normality	Multivariate ARCH	Multivariate normality	Multivariate ARCH
(S&P, Brazil SPI)	0.000	0.004	0.000	0.656	0.000	0.000
(S&P, Russia SPI)	0.000	0.008	0.000	0.884	0.000	0.008
(S&P, India SPI)	0.000	0.000	0.000	0.676	0.000	0.002
(S&P, ShenZhen SPI)	0.000	0.002	0.000	0.048	0.000	0.010
(S&P, Shangha SPI)	0.000	0.002	0.000	0.502	0.000	0.100
(S&P, South Africa SPI)	0.000	0.004	0.000	0.970	0.000	0.002

VAR model	Panel B: Symmetric Granger causality		Panel C: Hatemi-J asymmetric causality between cumulative Positive Shocks		Panel C: Hatemi-J asymmetric causality between cumulative negative Shocks	
	Wald test	**5%**	**Wald test**	**5%**	**Wald test**	**5%**
S&P ↛Brazil SPI	4.806***	4.182	0.23	3.841	0.061	3.687
S&P ↛Russia SPI	45.405***	8.165	0.283	3.349	13.258***	3.447
S&P ↛India SPI	29.018***	8..395	0.039	4.445	0.001	3.97
S&P ↛ Shanghai SPI	13.137***	5.923	0.236	4.281	0	4.087
S&P ↛ Shenzhen SPI	15/849***	6.131	0.039	4.445	0.001	3.97
S&P ↛South Africa SPI	0.574	3.885	1.047	3.861	0.196	3.995

Note: we calculate the critical values for Wald statistics using bootstrapping simulation technique proposed by Hatemi-J(2012). The symbol A ↛ B means that A does not cause B.

Table 4: Symmetric and Asymmetric Granger Causality in Time Domain – from the BRICS Markets to the US Market

VAR model	Panel A: Symmetric Granger causality		Panel B: Hatemi-J asymmetric causality			
			between cumulative Positive Shocks		between cumulative negative Shocks	
	Wald test	CV 5%	Wald test	CV 5%	Wald test	CV 5%
Brazil SPI ↛S&P	0.09	3.865	3.086	3.832	5.984**	4.035
Russia SPI ↛S&P	3.193	8.036	0.23	3.841	0.061	3.687
India SPI ↛S&P	1.718	7.644	0.283	3.349	13.2***	3.447
Shanghai SPI ↛S&P	1.445	5.817	0.216	4.551	0.439	3.505
Shenzhen SPI ↛S&P	4.951*	5.703	0.089	4.586	0.291	3.616
South Africa SPI ↛S&P	1.932	4.1	1.047	3.861	0.196	3.995

Note: we calculate the critical values for Wald statistics using bootstrapping simulation technique proposed by Hatemi-J (2012). The symbol A ↛ B means that A does not cause B.

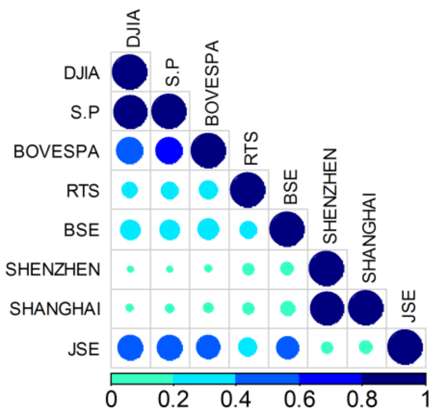

Figure 1: Spearman Correlation among Stock Market Indices

Note: Vertical axis is stock market and horizontal axis is Spearman correlation

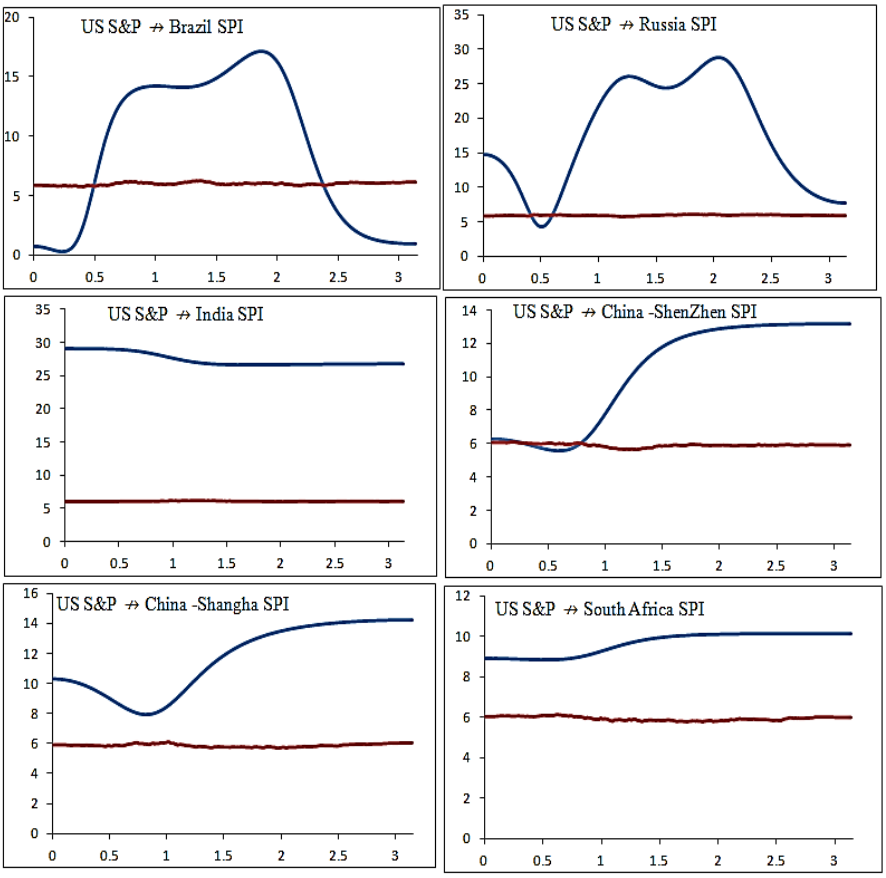

Figure 2: Symmetric Granger Causality from US Stock Market to the BRICS Stock Markets in the Frequency Domain

Note: Blue and red lines are Wald statistics and critical values at 5%, respectively. The symbol A ↛ B means that A does not cause B. Vertical and horizontal axes are Wald test statistics and frequency, respectively.

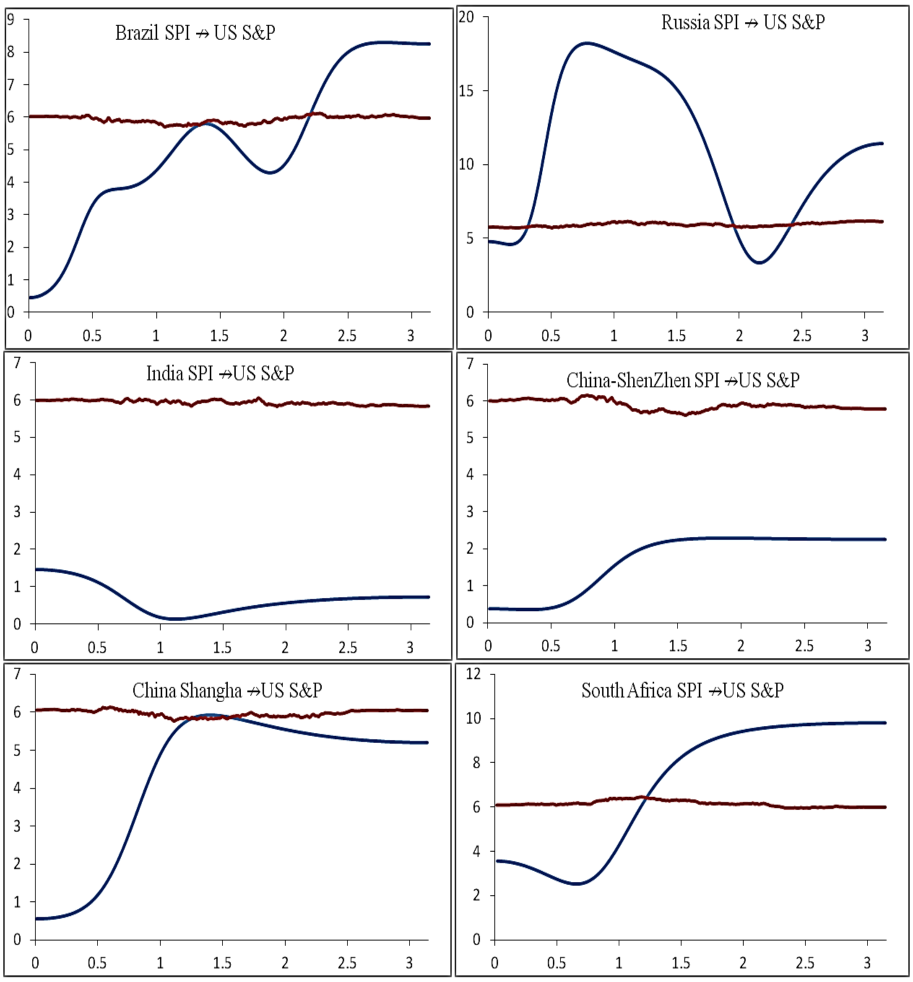

Figure 3: Symmetric Granger Causality from the BRICS Stock Markets to the US Stock Market in the Frequency Domain

Note: Blue and red lines are Wald statistics and critical values at 5%, respectively. The symbol A ↛ B means that A does not cause B. Vertical and horizontal axes are Wald test statistics and frequency, respectively.

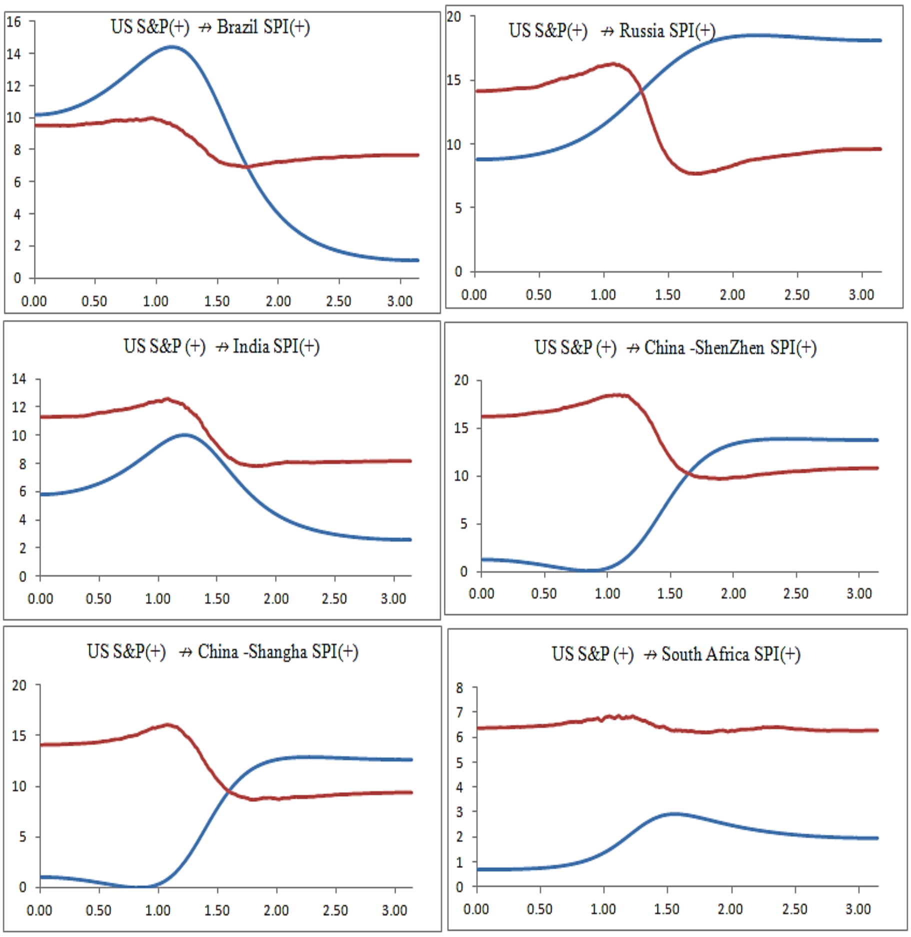

Figure 4: Asymmetric Granger Causality from Cumulative Positive Shocks of US S&P Series to Cumulative Positive Shocks of BRICS Countries SPI Series in the Frequency Domain

Note: Blue and red lines are Wald statistic and critical values at 5% respectively which are computed using bootstrap simulations of 5000 replications. The symbol A(+) ↛ B(+) means that cumulative positive shocks of A does not cause cumulative positive shocks of B. Vertical and horizontal axes are Wald test statistics and frequency, respectively.

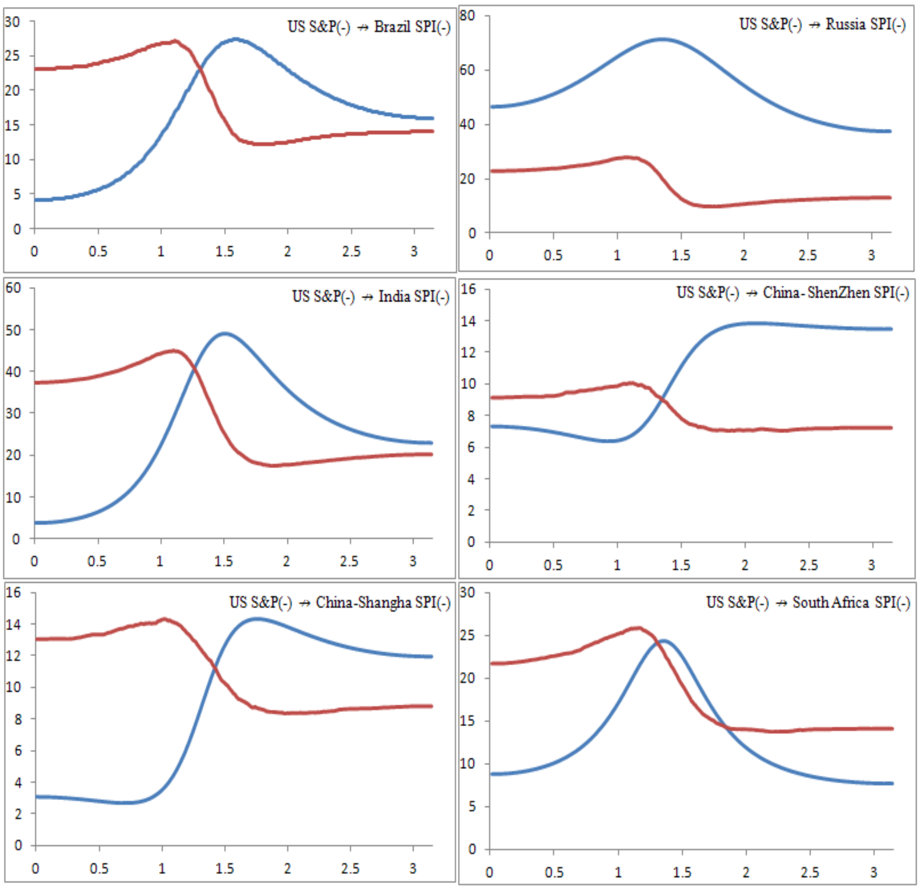

Figure 5: Asymmetric Granger causality from cumulative negative shocks of US S&P series to cumulative negative Shocks of BRICS countries SPI series in the frequency domain

Note: Blue and red lines are Wald statistic and critical values at 5% respectively which are computed using bootstrap simulations of 5000 replications. The symbol A(-) ↛ B(-) means that cumulative negative shocks of A does not cause cumulative negative shocks of B. Vertical and horizontal axes are Wald test statistics and frequency, respectively.

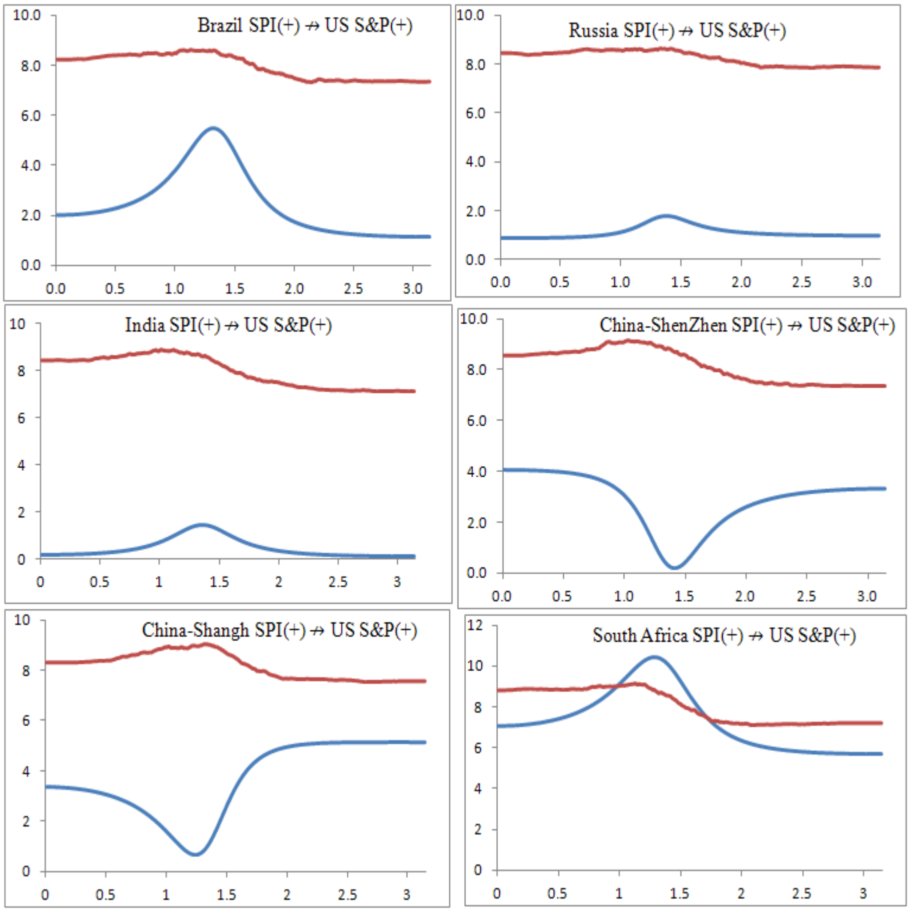

Figure 6: Asymmetric Granger Causality from Cumulative Positive Shocks of BRICS Countries SPI Series to Cumulative Positive Shocks of US S&P Series in the Frequency Domain

Note: Blue and red lines are Wald statistic and critical values at 5% respectively which are computed using bootstrap simulations of 5000 replications. The symbol A(+) ↛ B(+) means that cumulative positive shocks of A does not cause cumulative positive shocks of B. Vertical and horizontal axes are Wald test statistics and frequency, respectively.

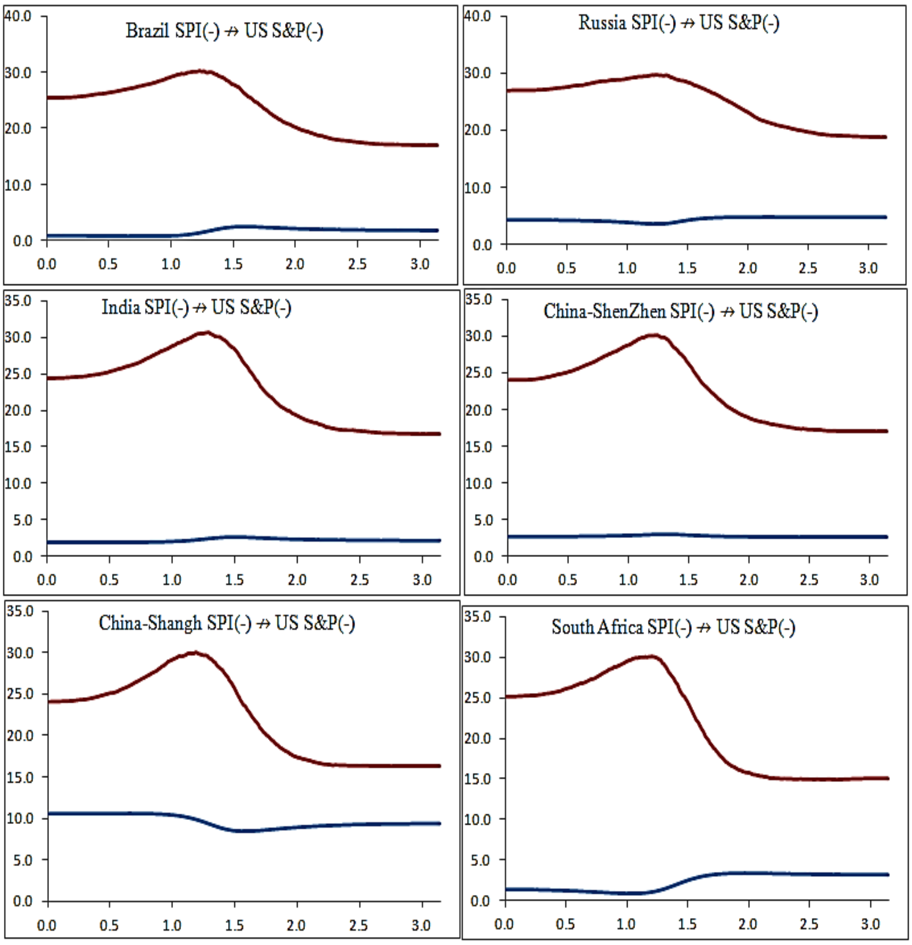

Figure 7: Asymmetric Granger Causality from Cumulative Negative Shocks of BRICS Countries SPI Series to Cumulative Negative Shocks of US S&P Series in the Frequency Domain

Note: Blue and red lines are Wald statistic and critical values at 5% respectively which are computed using bootstrap simulations of 5000 replications. The symbol A(-) ↛ B(-) means that cumulative negative shocks of A does not cause cumulative negative shocks of B. Vertical and horizontal axes are Wald test statistics and frequency, respectively.

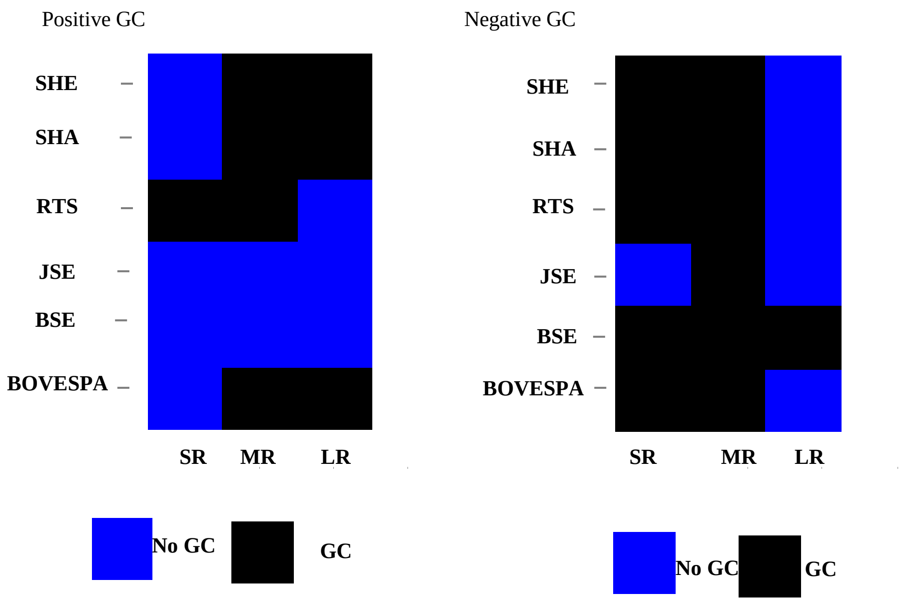

Figure 8: Summary - Negative GC from the US Stock Market to BRICS Stock Markets

Notes: no GC and GC are any Granger causality and Granger causality. Vertical and horizontal axes are stock markets and causality in short, medium, and long run, respectively.