1. Introduction

The 2010–2019 decade was quite interesting in terms of macroeconomics and the environment in which financial markets exist. During and after the Great Recession of 2007–2009, banks already had to save the economy by limiting financial risks, as well as keep interest rates low for many years. In addition, the role of regulators in many segments of the economy increased. Because of this macro environment and the ability of the central bank to reduce risks, there was a surprising increase in the value of companies in many countries. Moreover, cryptocurrencies, new financial technologies, and payment services received a powerful boost in the 2010s. This decade is unique given the longest-running ‘bull market’ in the United States and the resultant growth of the US economy for consequent 10 years. Since the US market strongly influence the other stock markets, with a decade of positive market growth, the global economy has not experienced negative volatility spillover effects from the US market. Consequently, the Russian, Indian, and Chinese markets grew under the influence of their own economic situation and the effects of volatility from other markets. From 2014 to 2015,
Russia and India experienced an economic crisis, and the Chinese stock market began to open up. The Chinese stock markets faced a crisis in 2015 as a result of the mortgage bubble burst. Since 2018, there was a lasting trade war between the United States and China, affecting a big number of emerging economies. All these events had a significant impact on the volatility of markets – including commodity and money markets – in other countries.

The study examines the relationship between the stock markets of the Russia–India–China (RIC) triad and the US market, the volatility spillover effects, and correlations between the markets of these countries. The work considers four periods from 2010 to the end of 2019 to directly trace the dynamics in the relationship between the markets in order to demonstrate the change in the transmission of volatility in the markets depending on the events.

Most scientific papers on this topic (e.g., (Dania, Malhotra, 2013; Gilenko, Fedorova, 2014; Kocaarslan et al., 2018; Konradsson, Pors, 2019; Panda, Thiripalraju, 2018; Patra, Panda, 2019; Singh, Tripathi, 2016; Syriopoulos et al., 2015; Tripathy, Gilaama, 2015)) study the periods of almost 20 years, which include the events of the 2008–2009 financial crisis, as well as its consequences. Consequently, the authors note high volatility spillover from the US to the developing country markets, for example, in the work by (Li, Giles, 2014). Most studies based only on emerging markets in the BRICS countries, for example, the authors (e.g., (Dania, Malhotra, 2013; Patra, Panda, 2018)) show a strong relationship between the markets of Russia, Brazil, and India, but weak integration between China and the global stock market.

This article proposes the following hypotheses. First, the Chinese market, in the 10 years beginning with its liberalization, quickly turned out to be a key player in the international financial market and became one of the sources of volatility. The impressive growth of the Chinese economy in recent decades quickly made it the first largest economy in the world, whereas the liberalization and integration of the Chinese stock market in the world stock exchanges that followed the economic boom could not be unnoticed by the scientific community. In particular, the article by (Baum, Kurov, Wolfe, 2014) examines the impact of news about changes in China’s macroeconomic indices on the global foreign exchange market. (Kirkulak, Khurshid, 2019) examine the impact of the Chinese stock market on the G7 markets. Specifically, the authors of this work give examples of the mutual influence of these stocks on each other. So they conclude that the Chinese market is more integrated into the world economy, than it was previously thought. A. Majdoub and B. Sassi (Majdoub, Sassi, 2017) provide another example of the significant influence of the Chinese market on the markets of neighboring Asian countries. It can be concluded based on the results of the above articles: with a further increase in integration and liberalization the Chinese market will continue influence not only the stock markets of neighboring countries, but will quickly spread it to the world stock market.

Second, with the reciprocal sanctions on Russia of the developed countries, the Russian stock market, which was heavily dependent on the US market, became less connected with it (Asaturov, Teplova, Hartwell, 2015).

Third, the authors also check the assumption that as a result of the trade war between the United States and China, a significant redistribution of the financial market and a reformatting of trade and economic ties happened, in turn increasing the vo-
Volatility spillover between the Russia–India–China triad and the United States

Volatility spillover effects between financial markets. The examples of the negative impact of the U.S.–China trade war on Japanese multinational corporations are given in the work by S. Chang and coauthors (Chang et al., 2019) which is of particular interest. The most recent work is the case study by (Toan, Burggraf, 2020), which examines the change in the indices of the United States, China, and the G7 countries. In their work, the authors show how new risks arising from the trade war between the United States and China create strong uncertainty on trading floors and force investors to change their investment strategy.

The data for the decade was divided into four parts to achieve a result that supports the above hypotheses. The first part, from 2010 to the end of 2013, represents a relatively calm period without any serious crises. These years are characterized by a weak interconnection between markets, as well as a low level of innovation transfer and volatility spillover effects.

The second period, from January 2014 to May 2015, is characterized by the crisis in Russia and the opening up the Chinese stock market. Most stock market research (e.g., (Zhou, Zhang W., Zhang J., 2012; Dania, Malhotra, 2013; Gilenko, Fedorova 2014; Kocaarslan et al., 2018; Panda, Thiripalraj, 2018; Patra, Panda, 2019)) argues that the Chinese stock market is the least integrated into the global financial system. A distinguishing feature of this study is the increasing connection between markets during the period covered, especially on the part of China. Therefore, the period in concern is taken not from March 2014, when economic sanctions on the Russian economy began, but from January 2014, since market volatility was observed back in January–February due to events in Ukraine. Still more an additional number of calculated observations, which contributes to obtaining more reliable results.

The third period, from June 2015 to May 2016, coincides with the Chinese stock crisis, that affected the markets of other countries. Due to the significant economic overheating and initiation of the bubble in July 2015, China experienced a stock market crash that lasted until March 2016. The Chinese crisis affected all global trading floors. This explains the next periodization of the study, which begins in June 2015 and ends in May 2016, thus, the study fully covers the entire period of the crisis in China and, at the same time, collects a critically important number of observations for the model.

The fourth period, from June 2016 to December 2019, is characterized by trade wars between the United States and China and the beginning of economic stagnation. During this period, world stock market indices updated historical lows and highs, and the countries that remained on the sidelines of the main trade confrontation were able to increase profits and deprive the once major exporters and importers of their leadership in many sectors of the economy. As is well known from economic theory (e.g., (Longin, Solnik, 1995)), markets can be highly correlated when a strong shock occurs in one of them because the shock will be transmitted from market to market. Accordingly, the strong impact from ‘bad news’ and volatility spillover effects would theoretically be relatively higher in the fourth period.

Research papers on the theme of volatility spillover effects are extremely diverse. This is directly related to the fact that the software for calculating programs has improved in recent years along with quantitative and qualitative enhancements in published statistics. For a combination of these reasons, finding all the necessary data and making basic calculations for almost any country in the world is no longer a difficult task.
Studies on the integration of stock markets first appeared in the 1980s, when researchers found that markets were mutually responsive and the US market played a leading role among all developed countries. The pioneering articles were written by (Engle, 1982; Bollerslev, 1986) using a then new autoregressive conditional heteroscedasticity (ARCH) model, which today remains the basic model for detecting dependencies. Subsequently (Hamao, Masulis, Ng, 1990; Neumark, Tinsley, Tosini, 1991) noted the undeniable influence of US stock markets on the volatility of markets in other countries. However, most major volatility transmission studies of the 1990s only considered market indicators of developed countries (e.g., (Bekaert, Wu, 1997; Hamao et al., 1990; Longin, Solnik, 1995)). Indicators of emerging capital markets included in the analysis were only in a few articles. They were traditionally assumed to be completely dependent on the movement of stock prices in developed countries with no independent impact on the other markets.

Research involving developing countries emerged in the early 2000s (e.g., (Fabozzi, Tunaru, Wu, 2004; Ledoit, Wolf, 2003; Sharkasi, Ruskin, Crane, 2005; Walid et al., 2011)). These papers consider volatility transmission in developing countries. R. Bhar and B. Nikolova (Bhar, Nikolova, 2007, 2009) investigated volatility in the BRIC countries using the ARMA (1, 1) GARCH (1, 1), and EGARCH models for this purpose. In their work, R. Bhar and B. Nikolova (Bhar, Nikolova, 2007) calculate secondary returns and volatility. This study revealed that the Brazilian market was positive to volatility spillover effects from the US stock market. A similar result was obtained for stock indices in India, where the regional transmission of volatility from the Asia Pacific region was higher than internationally. A 2007 study showed the positive aspects of diversification into the BRIC countries. The authors observe negative spillover effects from the Chinese market to the Asia Pacific region, and find volatility spillover from the European market to the Russian market. The article by (Bhar, Nikolova, 2009) studied the level of integration and dynamic relations between the world and the BRIC countries. The results of the EGARCH model in that article showed that India demonstrated the highest integration rate among the countries considered, followed by Brazil, Russia, and China.

It is worth noting that the Russian market is included in a quite small number of studies on volatility. For example, (Saleem, 2009) shows two-way volatility spillover effects between the Russian and US stock markets before the 1998 crisis, using a BEKK GARCH model. (Caporale, Spagnolo, 2011) noted volatility spillover effects from the UK and Russian markets to the countries of Central and Eastern Europe, using a VAR GARCH model.

The authors (Gilenko, Fedorova, 2014) examine volatility spillover effects in BRIC countries from 2003 to 2012, using a full BEKK GARCH design model. For a comprehensive study, the period was divided into three parts: pre-crisis, crisis, and post-crisis. The study results showed the dynamics of volatility spillover effects and the changes in the diagonal indicators of the BEKK GARCH matrix.

In another similar work, the authors (Li, Giles, 2014) studied the dynamics of volatility spillover between Asian countries and the United States using a full asymmetric BEKK model. The authors considered a study period of more than 20 years, 1993 to 2012, which was divided into three parts, as in (Gilenko, Fedorova, 2014). The results revealed that the US market was the main source of volatility in Asia, with two different effects of the stock market shock.
P. Felipe (Felipe, 2009) devoted a complete work dedicated exclusively to volatility transmission. It examines the transmission of shocks from terrorist attacks in the New York, Madrid, and London markets using a VAR BEKK GARCH model. This study made significant contributions to the research on volatility transmission and volatility spillover effects.

The authors (Bala, Takimoto, 2017) analyze the impact of the global financial crisis from 2007 to 2009 on emerging (Brazil, Hong-Kong, and Nigeria) and developed (United States, Japan, and UK) markets. The authors compare and demonstrate the analytical capability of various multivariate-GARCH (MGARCH) models and their variants. The results of the DCC GARCH model show improved correlation diagnostics compared to the other MGARCH models, partly because the fat tails and skewed features often present in the returns were considered.

Summarizing the results of this literature review, it should be noted that the theme of volatility transmission and volatility spillover effects are quite popular for researchers, and one often finds articles on regional markets. Over the years, authors showed a preference to study emerging and developed markets together to see the dynamics and distinctive features of a particular type of market, which, in turn, is necessary for portfolio investment diversification. Also, when performing calculations, one should be careful in choosing models to get the correct result. Most authors use the ARMA/GARCH models and their variations. Unfortunately, these models are prone to the so-called curse of dimensionality, which can lead to incorrect results.

The other parts of this article are structured as follows. Section 2 presents the methodology and describes the calculated data, Section 3 provides an empirical analysis of the results, and Section 4 provides general conclusions drawn from the research.

2. Materials and methods

The first attempts at modelling and predicting the market date back to the 1960s. Currently, there are three main models for calculations: macroeconomic based on vector autoregression, and dynamic stochastic. Note that these are only three main approaches, each of which contains a large number of models and their variations. In a VAR model, the presented a time invariant covariance matrix with an unobservable zero mean white noise vector process (Li, Giles, 2014). VAR modelling was originally proposed by C. Sims (Sims, 1980). This approach, in fact, relies on the use of information from the recent past to extrapolate the findings to future periods. In its standard form, VAR model is a system of econometric equations that describe the joint dynamics of several time series. The current value of each endogenous variable, according to such a model, depends on its own as well as other model variables’ past values.

E. Fama and B. Mandelbrot (Fama, 1965; Mandelbrot, 1963) noted that the asset returns in the stock market could represent ‘clustering volatility’. This means that volatility and its impact could be analyzed and predicted from spillovers. One of the first and most important papers to suggest the models for spillover calculation is (Engle, 1982), which presented ARCH models, followed by generalized ARCH (GARCH) models proposed by T. Bollerslev (Bollerslev, 1986). Thus, it can be stated that multidimensional GARCH models are widely used both for scientific purposes, for the analysis of secondary effects and markets, and for forecasting.

T. Bollerslev, R. Engle and J. Wooldridge (Bollerslev, Engle, Wooldridge, 1988) presented a new vector error-correction (VEC) model for more accurate predictions.
This model should preferably be used with a large number of calculation parameters. T. Bollerslev (Bollerslev et al., 1988) then proposed a simpler diagonal VEC model that did not need to compute large amounts of data. However, use of this model was limited, because it did not show the secondary effects between financial assets and the result of the model calculations — the $H_t$ matrix — could be definitely positive. According to (Engle, Kroner, 1995), the full BEKK GARCH model is capable of capturing the volatility spillover effect:

$$H_t = C'C + A'e_{t-1}e_{t-1}'A + B'H_{t-1}B,$$

where the off-diagonal elements of the matrices show the relationship between financial assets or markets and the secondary effects of conditional volatility. After (Engle, Kroner, 1995) full BEKK GARCH model, an expanded version of the full asymmetric BEKK GARCH model was soon proposed by K. Kroner and V. Ng (Kroner, Ng, 1998):

$$H_t = C'C + A'e_{t-1}e_{t-1}'A + B'H_{t-1}B + G'e_{t-1}e_{t-1}'G.$$

This is a modified full BEKK GARCH model, but matrix A, for more extended analysis, shows the reaction to innovations, the G matrix shows the effect of ‘bad news’, and matrix B measures the effects of past volatility. Accordingly, the diagonal elements express the influence of their own innovations, and the off-diagonal elements show the influence between the indices.

From the entire spectrum of GARCH models, it is BEKK GARCH that calculates the direct influence of the parameters on each other. BEKK GARCH that can reveal the interactions between parameters hidden in the data history (Huang, Su, Li, 2010). Thus, other modifications of the model, for example, DCC GARCH, demonstrate how mutual shocks correlate with the studied parameters, which does not quite fit the goals set by this study. All the mentioned models can calculate the variables of only two parameters, which introduce a certain limitation on the study. Based on the capabilities of the entire GARCH class of models, only BEKK GARCH can calculate more than two parameters. Moreover, the implemented covariance model can be used to calculate volatility spillover effects, but for calculations in this model, market micro-data is taken and not daily stock indices.

The full asymmetric BEKK GARCH model is estimated herein using the logarithmic maximum likelihood function:

$$L_n = -0.5n \ln(2\pi) - 0.5 \ln|H| - 0.5e'H^{-1}e,$$

where $n$ is the dimension of the model (equal to 4 in this case).

### 3. Results

#### 3.1. Data

The period from January 2010 to December 2019 was characterized by a bull market in the United States, which is reflected in the database of the entire decade. Therefore, one can see how the transfer of innovations between the markets changed. This study is designed to show how the dynamics of volatility transmission between communication markets change with events such as the opening up of the Chinese market in 2014, the crises in Russia and China, and the increase in volatility spillover effects from the trade war between the United States and China.

Consider in more detail how the time series is divided into periods and on what basis.
First period (January 2010 to December 2013): A relatively calm period for the RIC and US markets. This period witnesses the recovery of the international economy after the 2008 crisis.

Second period (December 2014 to May 2015): Russia faces economic and political instability with further sanctions imposed by the developed countries.

In 2014, the Chinese government approves the liberalization and opening up of the market to foreign investors.

Third period (June 2015 to September 2016): The crisis in the Chinese stock market.

Fourth period (from October 2016 to December 2019): Trade war between the United States and China; the global economic stagnation begins; decrease in key rates around the world.

This study includes daily market indices of countries at the close in local currencies (2511 observations): NYSE (US), RTSI (Russia), NIFTY (India) and SSE Composite (China). Note that the exchanges under consideration operate in different time zones, but since the data consists of daily indices and the number of hours between the cessation of trading in each country did not exceed 24 hours, it made possible to use the indices for calculation without making additional changes. Figure 1 presents the time series of stock market indices and returns. The figure clearly shows periods of volatility, especially during the Chinese stock crisis and the trade wars between the United States and China.

Russia, China and India were selected for this study, because these countries share a long history of cooperation within the framework of mutually beneficial agreements. The idea of creating a political and economic union “Moscow–Delhi–Beijing” was announced more than 20 years ago by Yevgeny Maksimovich Primakov, who was then Prime Minister of the Russian Federation. The leaders of the countries of this format are in favor of strengthening the role of developing countries in the system of managing the world economy. Moreover, Russia, India and China interact closely enough with each other. According to the assessment of the effectiveness of economic ties, trade turnover between the countries is very high. Therefore, China was the number one trading partner for several years for Russia, while Russia is among the top 10 countries in terms of trade relations for China. In turn, China is the second-largest business partner for India as well (Figure 2).

The NYSE is seen as a benchmark index, as well as a key player in the global market. Considering that each country has different number of working days, we substitute the data for three other indices into the working calendar of the NYSE stock exchange. To fill in the gaps in the data, we perform an interpolation routine. Stock market returns are calculated from the data using the following formula:

\[ r_{index} = \frac{index_t - index_{t-1}}{index_{t-1}}. \] (4)

Then, the estimated returns are used as data for calculating the VAR model. First, however, the lag-order selection test should be carried out in advance to understand which lag is better for the VAR model. According to the test results, five lags are best for the first and third periods, two lags for the second period, and one lag for the fourth period. Let us check the obtained residuals for stationarity using the Dickey–
Fig. 1
Time series of stock market indices and returns of NYSE (US), RTSI (Russia), NIFTY (India), and SSE Composite (China), January 11, 2010 to December 31, 2019

Fig. 2
Export and import trade value of goods (in billions of US dollars) for Russia, China and India, 2010 to 2019
Source: Data was taken from the World bank website.
Fuller test and the normal distribution. To obtain the p-value, we first calculate the standard error, and then apply the Wald test. Wald’s test results are shown in the table of results in parentheses. Table 1 presents the statistics of returns for each period.

Table 1 shows that the standard deviations of the indices in the second and third periods are fairly high. Table 2 well illustrates that the correlation of returns fluctuates between different periods. Thus, the correlation between RTSI and other indices is significantly lower in the second period, from January 2014 to May 2015, due to strong fluctuations in the Russian stock market. As for the SSEC index, the correlation increases in the third period, characterized by the Chinese stock crisis. The correlation between returns suggests volatility transmission during these periods.

### Table 1
Summary statistics for the returns series

| Index     | NYSE_ | RTSI  | SSEC | NIFTY |
|-----------|-------|-------|------|-------|
|           | Jan. 2010–Dec. 2013 |       |      |       |
| Obs.      | 1006  | 1006  | 1006 | 1006  |
| Mean      | 0.0004136 | 0.0000676 | –0.0003426 | 0.0002543 |
| Max       | 0.0525046 | 0.0703895 | 0.0694621 | 0.0496589 |
| Min       | –0.0705074 | –0.0861165 | –0.0658838 | –0.0408318 |
| Standard deviation | 0.0113928 | 0.016879 | 0.0128258 | 0.0117494 |
| Skewness  | –0.3731651 | –0.300737 | –0.1932586 | 0.2088017 |
| Kurtosis  | 6.909929 | 5.459983 | 5.850242 | 3.747266 |
| Median    | 0.0008193 | 0.0006098 | –0.0000565 | 0.0000247 |
|           | Jun. 2015–Sep. 2016 |       |      |       |
| Obs.      | 355   | 355   | 355  | 355   |
| Mean      | 0.0001983 | –0.0008297 | 0.002299 | 0.0008602 |
| Max       | 0.0215127 | 0.1416355 | 0.0622601 | 0.029873 |
| Min       | –0.0228786 | –0.1241369 | –0.0650463 | –0.029964 |
| Standard deviation | 0.0071539 | 0.0241917 | 0.01386602 | 0.00869 |
| Skewness  | –0.2973893 | –0.0276759 | –0.1057452 | –0.1366493 |
| Kurtosis  | 3.772938 | 10.08709 | 7.538187 | 3.865185 |
| Median    | 0.0003359 | –0.0001621 | 0.0014515 | 0.0004741 |
|           | Jun. 2015–Sep. 2016 |       |      |       |
| Obs.      | 338   | 338   | 338  | 338   |
| Mean      | –0.000041 | 0.0003195 | –0.0011638 | 0.0001144 |
| Max       | 0.0296398 | 0.0937797 | 0.0778815 | 0.0393225 |
| Min       | –0.0430084 | –0.0577353 | –0.0849065 | –0.059151 |
| Standard deviation | 0.0101303 | 0.0204208 | 0.0217359 | 0.01026 |
| Skewness  | –0.4274005 | 0.3818983 | –0.7734729 | –0.4846022 |
| Kurtosis  | 4.521284 | 4.348001 | 6.034746 | 6.610085 |
| Median    | 0.0000415 | –0.0001366 | 0.0006721 | 0.0002082 |
3.2. Evidence of stock market linkages

Before consideration of the model results, a more detailed discussion about the volatility of financial time series would be worthwhile. According to financial theory, the price of an asset should be equal to the expected present value of the future earnings on the asset. Following the expectations of investors, the price of an asset changes as new information about the asset is received, so the price of the asset and therefore income are random variables, implying volatility. The quality and quantity of new information

| Index | NYSE | RTSI | SSEC | NIFTY |
|-------|------|------|------|-------|
| Mean  | 0.0003477 | 0.0006007 | 0.000071 | 0.000438 |
| Max   | 0.0409219 | 0.0426907 | 0.0574038 | 0.0531911 |
| Min   | -0.0391598 | -0.1144378 | -0.0581463 | -0.038276 |
| Standard deviation | 0.0070333 | 0.0124525 | 0.0105836 | 0.0080192 |
| Skewness | -0.6681596 | -1.075863 | -0.223906 | 0.1722028 |
| Kurtosis | 7.820061 | 12.42654 | 8.616448 | 6.661591 |
| Median | 0.0006236 | 0.0008094 | 0.0005038 | 0.0005323 |

Note. NYSE (US), RTSI (Russia), NIFTY (India), and SSEC (China).

Table 2

Correlations between stock market indices

| Index | NYSE | RTSI | SSEC |
|-------|------|------|------|
| RTSI  | 0.5249 |      |      |
| SSEC  | 0.1342 | 0.2457 |      |
| NIFTY | 0.2885 | 0.4354 | 0.194 |
| Jan. 2010–Dec. 2013 |
| RTSI  | 0.3900 |      |      |
| SSEC  | 0.0223 | -0.0190 |      |
| NIFTY | 0.2148 | 0.2172 | 0.0717 |
| Jan. 2014–May 2015 |
| RTSI  | 0.5354 |      |      |
| SSEC  | 0.2266 | 0.2361 |      |
| NIFTY | 0.4486 | 0.4668 | 0.2639 |
| June 2015–Sep. 2016 |
| RTSI  | 0.3019 |      |      |
| SSEC  | 0.1564 | 0.1753 |      |
| NIFTY | 0.1531 | 0.1388 | 0.1919 |
| Oct. 2016–Dec. 2019 |

Note. NYSE (US), RTSI (Russia), NIFTY (India), and SSEC (China). Significance level: 5%.
or shocks change over time; for example, a severe shock or crisis generates negative news, building a cluster of negative information. Likewise, economic growth creates a cluster of positive information. Thus, the market reacts to a cluster of different types of news with a cluster of high or low volatility (Bauwens, Hafner, Laurent, 2011; Engle 2004). The first person to formulate this concept was B. Mandelbrot (Mandelbrot, 1963): “large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes” (p. 418).

Now let us analyze the results of the full asymmetric BEKK GARCH (1,1,1) model in Table 3. High diagonal coefficients of matrix B, almost equal to 1, show a classic characteristic for financial data — high stability of volatility in its own market. Matrix A shows the reaction to general spillovers. If matrix A is smaller than matrix G, negative news will have a stronger impact on the market than general news.

A volatility spillover effect from the American to the Russian market was recorded in the first period, from January 2010 to December 2013, at 0.0322. This result once again confirms the then-prevailing research theme that the American market strongly influenced the Russian market. The coefficients for all markets show the relationship between the markets and the reaction to general shocks in matrix A and ‘bad news’ from matrix G.

The second period includes events related to the onset of the political and economic crisis in Russia and the imposition of targeted sanctions on the banking sector, massive strikes in India, and the first steps of liberalization in the Chinese stock market. Consequently, the third period witnesses a strong increase in volatility transfer rates and shocks on volatility, particularly the ‘bad news’ in matrix G. This is especially evident between G (3.2) and G (3.4), which implies that two assets carrying negative news at the same time should increase the variance of the market. Matrix B also shows a gradual increase in volatility spillover effects between markets. As expected, all the markets reacted to the crisis during this period, as evident from the negative shock from the Chinese market in matrix G.

In the fourth period, the variance of the NYSE index returns increases with the covariance of indices, as shown in matrix B, which indicates that all world markets are closely integrated with the American market. The reasons for this lie in the trade war between the United States and China, coupled with the global stagnation and a decrease in the key rates. An analysis of the dynamics involved suggests that a record lowering of the key rates, coupled with the high integration of the American market into world processes, led to a serious increase in the volatility spillover effects on all markets. An examination of other countries’ indices shows that the Russian, Indian, and Chinese financial markets are highly interconnected, leading to volatility transmission between them in the event of negative shocks, further complicating the diversification of portfolio investments.

4. Discussion

Similar studies on volatility transmission spillover effects (e.g., (Bhuyan et al., 2016; Gilenko, Fedorova, 2014; Panda, Thiripalraju, 2018; Patra, Panda, 2019; Syriopoulos et al., 2015)) spanned the events of the 2008 financial crisis, which therefore greatly affected their results. However, the goal of this work, in principle, was not to touch on the recent financial crisis, but to consider the behaviour of mar-
Table 3.
Estimation results of the full asymmetric BEKK GARCH model

| Index          | Matrix A                  | Matrix G                  | Matrix B                  |
|----------------|---------------------------|---------------------------|---------------------------|
|                | NYSE, \(j=1\) | RTSI, \(j=2\) | SSEC, \(j=3\) | NIFTY, \(j=4\) | NYSE, \(j=1\)  | RTSI, \(j=2\) | SSEC, \(j=3\) | NIFTY, \(j=4\) | NYSE, \(j=1\)  | RTSI, \(j=2\) | SSEC, \(j=3\) | NIFTY, \(j=4\) |
| NYSE, \(i=1\) | 0.116  | 0.0315 | 0.0196  | -0.0474 | 0.1185 | -0.0167 | 0.0203  | -0.0309 | 0.9449 | 0.0322 | 0.0015 | -0.0075 |
|                | (0.3865) | (0.1736) | (0.4728) | (0.5461) | (0.0009) | (0.0928) | (0.0444) | (0.0937) | (0.0000) | (0.0000) | (0.0024) | (0.3472) |
| RTSI, \(i=2\) | -0.0195 | 0.0875 | 0.0097  | -0.0002 | -0.0052 | 0.157 | -0.0145 | -0.017 | -0.0168 | 0.9413 | 0.002 | 0.006 | -0.005 |
|                | (0.0155) | (0.2553) | (0.5582) | (0.3636) | (0.3727) | (0.1289) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| SSEC, \(i=3\) | -0.0092 | 0.0369 | 0.0865  | -0.0074 | 0.0179 | 0.019 | 0.1096 | 0.0052 | 0.0032 | -0.0118 | 0.9479 | 0.0238 |
|                | (0.0006) | (0.6806) | (0.0184) | (0.2929) | (0.2388) | (0.0023) | (0.1289) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| NIFTY, \(i=4\) | -0.0216 | -0.0062 | 0.0194  | 0.0871 | 0.0065 | 0.0161 | 0.0059 | 0.1283 | 0.0001 | -0.0057 | -0.0279 | 0.9318 |
|                | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.4700) | (0.5714) | (0.2355) | (0.0000) | (0.0001) | (0.0019) | (0.0000) | (0.0000) |

January 2014–January 2015, second period

| Index          | Matrix A                  | Matrix G                  | Matrix B                  |
|----------------|---------------------------|---------------------------|---------------------------|
|                | NYSE, \(i=1\)  | RTSI, \(i=2\)    | SSEC, \(i=3\)  | NIFTY, \(i=4\)  | NYSE, \(i=1\)  | RTSI, \(i=2\) | SSEC, \(i=3\) | NIFTY, \(i=4\)  | NYSE, \(i=1\)  | RTSI, \(i=2\) | SSEC, \(i=3\) | NIFTY, \(i=4\)  |
| NYSE, \(i=1\) | 0.0808 | 0.017 | -0.0028 | -0.0116 | 0.1123 | 0.0185 | -0.003 | -0.0129 | 0.9403 | -0.0307 | 0.0053 | 0.0059 |
|                | (0.0000) | (0.2334) | (0.2984) | (0.2824) | (0.0000) | (0.0002) | (0.0000) | (0.2408) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| RTSI, \(i=2\) | 0.0187 | 0.1175 | -0.0213 | 0.0079 | -0.0007 | 0.1291 | -0.0027 | -0.0306 | -0.0517 | 0.9427 | -0.0385 | -0.0022 |
|                | (0.0009) | (0.0000) | (0.0000) | (0.0000) | (0.0488) | (0.0000) | (0.1921) | (0.0043) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| SSEC, \(i=3\) | -0.0515 | 0.0053 | 0.0255 | -0.0005 | 0.0252 | 0.0083 | 0.1088 | 0.0519 | 0.0054 | 0.0467 | 0.9391 | -0.0069 |
|                | (0.0000) | (0.0179) | (0.0000) | (0.2267) | (0.0514) | (0.0156) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| NIFTY, \(i=4\) | 0.0017 | 0.0317 | 0.0184 | 0.0376 | -0.0313 | -0.0111 | 0.0146 | 0.1475 | 0.028 | 0.0161 | 0.0207 | 0.9422 |
|                | (0.0212) | (0.0254) | (0.0628) | (0.0012) | (0.0051) | (0.2350) | (0.1701) | (0.0000) | (0.0000) | (0.0000) | (0.0672) | (0.0000) |
### June 2015–September 2016, third period

| Index | Matrix A | | | Matrix G | | | Matrix B | | |
|---|---|---|---|---|---|---|---|---|
| NYSE, \(j=1\) | 0.0186 | -0.0614 | -0.0488 | -0.0684 | 0.1534 | 0.0576 | 0.0249 | 0.0572 | 0.9392 | -0.0121 | -0.0002 | 0.0656 |
| \(p=0.7960\) | \(p=0.0081\) | \(p=0.4125\) | \(p=0.0500\) | \(p=0.0059\) | \(p=0.5507\) | \(p=0.7560\) | \(p=0.6443\) | \(p=0.0000\) | \(p=0.0944\) | \(p=0.7887\) | \(p=0.0000\) |
| RTSI, \(i=2\) | -0.0662 | 0.0169 | -0.0460 | -0.0010 | 0.0426 | 0.1239 | 0.0135 | 0.0561 | 0.0030 | 0.9444 | 0.0593 | -0.0152 |
| \(p=0.0025\) | \(p=0.2283\) | \(p=0.0001\) | \(p=0.8727\) | \(p=0.0661\) | \(p=0.0000\) | \(p=0.6047\) | \(p=0.2048\) | \(p=0.5985\) | \(p=0.0000\) | \(p=0.0000\) | \(p=0.0185\) |
| RTSI, \(i=2\) | 0.0053 | 0.0186 | 0.0552 | 0.0309 | 0.0125 | 0.0824 | 0.1642 | 0.0541 | -0.0106 | -0.0146 | 0.9399 | 0.0519 |
| \(p=0.7332\) | \(p=0.0241\) | \(p=0.0002\) | \(p=0.0003\) | \(p=0.7292\) | \(p=0.0208\) | \(p=0.0000\) | \(p=0.0716\) | \(p=0.1038\) | \(p=0.0892\) | \(p=0.0000\) | \(p=0.0024\) |
| NIFTY, \(i=3\) | 0.0160 | -0.0286 | 0.0023 | 0.0456 | -0.0283 | -0.0447 | -0.0060 | 0.1218 | 0.0086 | -0.0010 | -0.0150 | 0.9394 |
| \(p=0.7146\) | \(p=0.1396\) | \(p=0.7986\) | \(p=0.0456\) | \(p=0.6002\) | \(p=0.3291\) | \(p=0.8764\) | \(p=0.0727\) | \(p=0.6306\) | \(p=0.7460\) | \(p=0.0319\) | \(p=0.0000\) |

### October 2016–December 2019, fourth period

| Index | Matrix A | | | Matrix G | | | Matrix B | | |
|---|---|---|---|---|---|---|---|---|
| NYSE, \(j=1\) | 0.0740 | -0.0063 | -0.0216 | -0.0062 | 0.1845 | -0.0229 | -0.0249 | 0.0512 | 0.9324 | 0.0071 | 0.0172 | 0.0195 |
| \(p=0.0000\) | \(p=0.1468\) | \(p=0.8473\) | \(p=0.4552\) | \(p=0.0000\) | \(p=0.8926\) | \(p=0.6164\) | \(p=0.3560\) | \(p=0.0000\) | \(p=0.6113\) | \(p=0.0353\) | \(p=0.0659\) |
| RTSI, \(i=2\) | 0.0217 | 0.0854 | 0.0250 | 0.0309 | 0.0185 | 0.2035 | 0.0012 | -0.0153 | 0.0127 | 0.9325 | 0.0272 | 0.0185 |
| \(p=0.0000\) | \(p=0.0511\) | \(p=0.4736\) | \(p=0.0001\) | \(p=0.7487\) | \(p=0.0000\) | \(p=0.9217\) | \(p=0.8129\) | \(p=0.0000\) | \(p=0.0000\) | \(p=0.1793\) | \(p=0.4080\) |
| RTSI, \(i=2\) | 0.0269 | 0.0043 | 0.0874 | -0.0048 | -0.0031 | -0.0250 | 0.2039 | 0.0111 | 0.0306 | -0.0316 | 0.9322 | -0.0133 |
| \(p=0.4456\) | \(p=0.7437\) | \(p=0.1273\) | \(p=0.8213\) | \(p=0.7899\) | \(p=0.4619\) | \(p=0.1574\) | \(p=0.8821\) | \(p=0.0000\) | \(p=0.0000\) | \(p=0.0000\) | \(p=0.0000\) | \(p=0.2090\) |
| NIFTY, \(i=3\) | -0.0226 | -0.0233 | -0.0147 | 0.0812 | -0.0131 | -0.0332 | 0.0225 | 0.2033 | -0.0240 | 0.0179 | -0.0211 | 0.9320 |
| \(p=0.7151\) | \(p=0.9245\) | \(p=0.8757\) | \(p=0.2461\) | \(p=0.7226\) | \(p=0.5870\) | \(p=0.5574\) | \(p=0.0000\) | \(p=0.0000\) | \(p=0.6770\) | \(p=0.2703\) | \(p=0.0000\) | \(p=0.0000\) |

*Note.* NYSE (US), RTSI (Russia), NIFTY (India), and SSEC (China). Round brackets show \(p\)-values from Wald test.
kets and their dynamics in the absence of serious global shocks. Moreover, the Chinese market, which was previously closed to foreigners, has officially begun the process of liberalization and opening up, since 2014, is poised to alter the world market conjuncture. Thus, (Patra, Panda, 2019; Dania, Malhotra, 2013) find a weak relationship between the Chinese and other world markets. The present research reflects the dynamics of the increasing influence of the Chinese market. Previous studies have found strong US market influence on the BRICS countries (Bhuyan et al., 2016), as well as on the Chinese (before the 2008 crisis) and Brazilian (during the 2008 crisis) markets (Gilenko, Fedorova, 2014). The other BRICS markets were exposed to the infection by volatility from other local leaders, Germany, and Japan. The authors’ results illustrate that the Russian, Indian, and Chinese markets are influenced by the US market, but the volatility spillover effects from the ‘main supplier of volatility’ may decrease significantly when one of the RIC countries faces a crisis and the transmission of ‘bad news’ begins from the emerging markets to the United States. Notably, this research shows that the US market has a significantly lower impact on the Russian market with the sanctions targeted at the Russian economic sector by the United States and other countries. This is the first study to examine the impact of economic sanctions on the change in the volatility spillover effects of the stock market. Another feature of this research is the division of the time series into four parts, a practice already adopted in the scientific literature — for example (Gilenko, Fedorova, 2014; Li, Giles, 2014). However, these studies consider the dynamics of volatility spillover effects before, during, and after the 2008 financial crisis. This study considered the dynamics of mutual influence between the RIC and US markets at a time when events in a particular country generated a high level of shock subsequently. One sees close integration and strong dependence — political dependence confirmed economically at the stock market level — between the Russian, Indian, and Chinese markets. Thus, ‘bad news’ from one market affects others, contributing to the volatility spillover effects within these three markets, which in turn are important for asset diversification. Also, F. Longin and B. Solnik (Longin, Solnik, 1995) conclude, in their basic study on the correlation between markets, that markets develop a high level of interconnection in the wake of strong shocks. Therefore, the current world economic situation can be summed up as follows. The trade war between the United States and China, on top of the stagnation of the world economy and the lowering of the key rates in most developed and developing countries, has seriously affected the trade relations between countries and markets. It is perceived as a strong shock and, instead of the desired stabilization, has resulted in volatility transmission between the markets.

In this article, we used low-frequency daily closing data, despite the fact that using intraday returns to calculate the BEKK GARCH model through the realized covariance estimators showed the best results. Similar to the article by J.F. Caldeira, G.V. Moura, M.S. Perlin, A.A.P. Santos (Caldeira et al., 2017), finding intraday returns over long periods for different indices is not possible, which is a significant omission for the scientific community.

4.1. Conclusion

The relationships between the stock markets of Russia, India, China, and the United States were analyzed herein. The effects of volatility spillover between stock indices, of the markets under consideration, were estimated using the VAR BEKK GARCH model for the period of January 2010 to December 2019.
In brief, the 2010–2019 decade provided a great opportunity to all financial markets in the developing world to enter a new growth stage. During ten years great changes in the financial market conjuncture were managed without strong shocks from the American market, which is traditionally considered a source of volatility, and shock news for the global financial market. This study tests three hypotheses. The first is associated with the post-2014 change, from weak to strong interconnection, between the Chinese stock market and the Russian and Indian markets. This is particularly evident in the Indian and Russian markets’ reaction to shocks from the Chinese market. Theoretically, volatility transmission, from the world’s largest economy, will only continue to increase with the rising political and economic role of the People’s Republic of China in the international affairs, producing a relevant topic for future research. The second hypothesis is: the Russian market became less dependent on the US market due to reciprocal economic sanctions between Russia and the developed countries. This hypothesis is also supported by the research. The third hypothesis, which was clearly demonstrated in the results of this study, argues that the trade war between the United States and China increased the volatility spillover effects between the financial markets. Thus, the actions taken against the Chinese economy will ultimately have a broad and profound effect on other markets, including those where these actions were initiated.

In summary, we can conclude that with the growing globalization of the world financial system, markets could become increasingly vulnerable to crises and other adverse economic events in highly uncertain economic conditions.

The results obtained from the research can be used not only for a deeper analysis of stock market processes and for understanding the global macroeconomic situation, but also for investment portfolio diversification and risk hedging by various financial organizations.

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Это исследование посвящено выявлению экономических связей и побочных эффектов волатильности рынков между США и триадой Россия–Индия–Китай с 2010 по 2019 г. Это десятилетие характеризуется отсутствием крупных глобальных финансовых кризисов в экономике, хотя либерализация китайского фондового рынка и ответные санкции между Россией и развитыми странами, за которыми последовали торговые войны между США и Китаем, изменили отношения между фондовыми рынками. Это исследование проверяет три гипотезы. Первая гипотеза связана с изменением после 2014 г. взаимосвязи китайского фондового рынка с рынками России и Индии. Вторая гипотеза проверяет, стал ли российский рынок менее зависимым от рынка США. Третья гипотеза: торговая война между Соединенными Штатами и Китаем усилила побочные эффекты волатильности между финансовыми рынками. Для расчетов использовалась многомерная модель GARCH BEKK. Представленные результаты исследования могут быть использованы для выводов об общей текущей ситуации на мировых фондовых рынках и тенденциях их дальнейшего развития, а также для более полного понимания механизмов взаимодействия и взаимовлияния финансовых рынков для возможной диверсификации финансовых рынков.

Ключевые слова: побочные эффекты волатильности; РИК; асимметричная модель BEKK; фондовый рынок; многомерный GARCH.

Классификация JEL: G1, G15.

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