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Assessing the financial interconnectedness between China and Russia: A dynamic approach[1]

Abstract. Our study investigates the dynamic connectedness and volatility spillovers between China and Russia, focusing on their economic and financial market interactions from 2009 to 2023. Utilizing a Time-Varying Parameter Vector Autoregression (TVP–VAR) and the LASSO models, we examine how bilateral trade influences financial markets, including stock indices, bond yields, and liquidity measures. We discover a moderate positive correlation between Chinese exports to Russia and the performance of Russian financial markets, highlighting a still nascent, but growing role of trade structures. The results also show that economic relations between China and Russia have substantial impacts on their respective financial markets, driven by evolving geopolitical and economic contexts. This study contributes to the understanding of international economic relations and financial market dynamics, providing insights into the mechanisms of volatility transmission and the interconnectedness of global markets.

Keywords: *volatility spillovers, China-Russia economic relations, time-varying parameter VAR (TVP–VAR), financial market dynamics, financial interconnectedness.*

JEL Classification: G12, G15.

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1. Introduction

Volatility spillovers can occur across various financial markets, including foreign exchange, stock markets, commodities, and industrial sectors (Choi, 2022; Liu, Gong, 2020). This interconnectedness suggests that local and global events can trigger volatility, influenced by multiple economic, institutional, and political factors. Financial markets are particularly sensitive to regulatory mechanisms and financial institutions, as investors' reactions to economic and political events can initiate volatility processes that interconnected markets might react to (BenSaïda, 2019; De Mello, Moccero, 2009). Long-term spillovers between interest rates, expected inflation, and inflation targets in regional markets highlight the influence of monetary policy on investors' sentiments (De Mello, Moccero, 2009). Unconventional monetary policies, such as quantitative acceleration, can generate more risky conditions for investors, leading to increased volatility (Tillmann, 2016). Additionally, new financial assets like

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cryptocurrencies are still in their early stages and are sensitive to regulations, which can cause spillovers (Pelagidis, Kostika, 2022).

Political environments also play a critical role in moderating the strength and duration of volatility spillovers. (Gungoraydinoglu, Çolak, Öztekin, 2017) identify the political environment as a key driver of information risk, transaction costs, and debt exposure across the globe. Financial policy regimes shape the intensity and possibility of volatility spillovers, with financial liberalization catalyzing these spillovers, particularly in emerging markets (Huo, Ahmed, 2017; Caporale, Hadj Amor, Rault, 2014). Volatility spillovers also vary across different geographic regions, influenced by the source of the crisis and the specific market involved (García, Rambaud, 2023). Emerging markets are more sensitive to global factors such as economic uncertainty and oil price volatility (Syed, Bouri, 2022).

International economic relations significantly contribute to the interconnections of financial markets, affecting stock prices, currency exchange rates, and commodities (Stockman, 1988). The magnitude of spillovers depends on the receiving country's trade and financial integration (Georgiadis, 2016). Tighter economic connections, such as bilateral trade, are more likely to cause transmissions of volatilities. The position of a country as an importer or exporter can also predict the source of volatility (You et al., 2024). Trade deficits increase foreign debt, decrease foreign reserves, and weaken confidence in domestic currency exchange rates, which can pretext global political and economic events (Ma, Cheng, 2005; Chatziantoniou, Floros, Gabauer, 2022). Peaks in volatility occur during periods of economic and financial instability (Morales-Zumaquero, Sosvilla-Rivero, 2018).

Economic relations are significant antecedents that cause and transmit volatility spillovers in international financial markets, especially during times of crisis. The current geopolitical situation acts as a catalyst for volatility. This study specifically analyzes the relations between China and Russia as a dynamic process explaining the quality of volatilities (Dedi, Yavas, 2016; Banerjee, Devereux, Lombardo, 2016; Sugimoto, Matsuki, Yoshida, 2014). The strategic importance of China–Russia trade relations is underscored by the increase in mutual trade volume and the shift towards conducting payments in national currencies, which separates their economic relations from other markets[2].

The demand for popular investment targets, such as U.S. equities and their substitutes, also plays a role in influencing stock prices and causing spillovers in financial markets (Liu et al., 2022). The global financial system has become highly complex, with extensive cross-border interconnections and interdependencies. In this interconnected environment, local financial shocks can be easily amplified and escalate into regional or global events (Raddant, Kennett, 2021). Numerous studies confirm that the interconnectedness of financial markets has increased due to globalization, macroeconomic policies, trade expansion, and technological advancements, highlighting significant research streams in financial market studies (Wang et al., 2021; Fang et al., 2021; Chowdhury et al., 2019). In this context, it is crucial for investors to pay greater attention to global events and account for their risks to manage portfolios effectively (Wang et al., 2023).

This is particularly relevant during times of geopolitical uncertainty because international economic relations, especially through trade, can impact financial mar-

[2] China customs official data (http://english.customs.gov.cn/Statics/01258a9c-e0c7–4080-b9e9–9c5faec13281.html).

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kets in diverse ways. The interconnectedness of economies through trade in goods, services, assets, and technologies can lead to volatility spillover effects on financial markets (Schiavo, Reyes, Fagiolo, 2010). This explains why global economic and political events can significantly change the landscape of international trade with implications for financial markets (You et al., 2024; Ma, Cheng, 2005). The contemporary context characterized by geopolitical instability underscores this issue. For instance, Russia's exclusion from global financial institutions and the growing significance of Russia–China trade relations necessitates scholarly reassessment. The influence of international trade indicators and foreign direct investments was extensively studied (Caporale et al., 2022). Financial development proactively affects international trade and manufacturing for exporting countries (Agbloyor et al., 2013). International trade and exchange rates can have spillover effects on stock market volatility and interconnectedness (Pan et al., 2007).

The relevance of this context is supported by the solid growth in China–Russia economic relations over the past decade. Despite Russia's economic isolation due to global sanctions, its economic relations with China intensified. In fact, mutual trade increased to $7.2 billion in 2022 from $4.3 billion in 2021[3]. Considering the reduction in Russia's overall international economic relations, it is assumed that this interdependence will only intensify in the future. Consequently, China–Russia relations will become more prominent in investors' decisions and the influence these decisions may have on financial markets. This study particularly examines the dynamic connectedness of stock markets driven by the intensification of bilateral economic activities and its effects on international economic relations, stock, and bond markets, as well as financial sector indicators.

To test whether the intensification of economic activities significantly influences the financial markets of the two countries, our study is grounded in two main research questions.

1. How do export and import activities between China and Russia contribute to volatility spillovers in their financial markets?

2. How does the growing interconnectedness of state economies influence volatility spillovers in their financial markets, and which market is more affected?

Despite the extensive body of research on volatility spillovers and financial market interconnectedness, several gaps remain that this study aims to address.

What do we not know from existing literature? — Firstly, while there is substantial evidence on volatility spillovers across various financial markets, such as foreign exchange, stock markets, commodities, and industrial sectors (Choi, 2022; Liu, Gong, 2020), the specific dynamics of these spillovers in the context of intensified bilateral trade relations between countries like China and Russia are less understood. Previous research did not fully explored how particular trade structures and economic policies influence spillovers in emerging markets. Secondly, while the literature highlights the sensitivity of financial markets to regulatory mechanisms and investor reactions to economic and political events (BenSaïda, 2019; De Mello, Moccero, 2009), there is limited analysis on how political environments, such as the recent geopolitical tensions involving Russia, affect the strength and duration of volatility spillovers (Gungoraydinoglu, Çolak, Öztekin, 2017; Huo, Ahmed, 2017). The unique situation of China maintaining trade relations with a globally sanctioned Russia provides a novel context for examining these dynamics.

[3] China Customs Statistics Office (http://english.customs.gov.cn/Statics/01258a9c-e0c7-4080-b9e9-9c5faec13281.html).

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Thirdly, although the role of international economic relations in causing and transmitting volatility spillovers is acknowledged (Stockman, 1988; Georgiadis, 2016), the specific mechanisms through which bilateral trade, trade deficits, and economic dependencies impact financial market dynamics require further investigation. Our study focuses on the trade relations between China and Russia, offering new insights into how their economic interdependence affects financial market volatility (Ma, Cheng, 2005; Chatziantoniou, Floros, Gabauer, 2022). Moreover, while there is some research on the impact of international trade and foreign direct investments on financial markets (Caporale, Hadj Amor, Rault, 2014; Agbloyor et al., 2013), there is limited empirical evidence on the dynamic connectedness and time-varying relationships between these factors and financial market indicators in the specific context of China–Russia relations. We address this gap by employing advanced econometric models such as TVP–VAR and LASSO to capture the evolving nature of these relationships (Diebold, Yilmaz, 2009, 2012; Foster, Verbyla, Pitchford, 2008). Finally, while previous studies have predominantly focused on stock returns, our research extends the analysis to include other financial assets like government bonds and financial sector indices (Mushafiq, 2023). This comprehensive approach helps to understand the full spectrum of financial interconnectedness and volatility transmission mechanisms in a globally interconnected economy.

The contribution of our study is twofold. First, it explains the factors behind volatility spillovers from the standpoint of international economic relations and their bilateral intensification. Second, it tests the dynamic effects of growing interconnection between the Chinese and Russian economies on stock and bond markets and the financial sector to enrich the existing discussion on market efficiency. Additionally, this study uses the context of Russia–China relationships as an experimental venue to explore the regionalization of international economic relations caused by geopolitical implications and their influence on financial markets.

Our paper is organized as follows: first, a literature review discusses the role of volatility spillovers and existing views on the influence of international economic connectedness on financial markets. It also examines the evolving economic relationships between Russia and China and provides insights into the development of their economic relations. Next, the model and data are discussed. The final part contains the findings and conclusions drawn from the analysis procedures.

2. Literature background

2.1. Volatility spillovers and global financial markets

Extant research shows that volatility spillovers can occur between similar (McMillan, Speight, 2010) and different financial markets, such as the foreign exchange market and the stock market, oil and gas commodities, and industrial sectors (Choi, 2022; Liu, Gong, 2020). This phenomenon occurs due to the interconnectedness of financial markets, where local and global events trigger volatility. This indication suggests that the antecedents of volatility spillovers are multifaceted and depend on various economic, institutional, and political factors.

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Fundamentally, financial markets are highly sensitive to regulatory mechanisms and financial institutions. Investors are sensitive to changes, and their reactions to economic and political events can initiate volatility processes that interconnected markets might react to. The quality of investors' expectations indicates the direction of spillover, where positive and negative shocks relate to good and bad volatility components, respectively (BenSaïda, 2019). L. De Mello and D. Moccero (De Mello, Moccero, 2009) demonstrated long-term spillovers between the interest rate, expected inflation, and the inflation target in regional markets, highlighting the influence of monetary policy on investors' sentiments. Unconventional monetary policy, as shown by (Tillmann, 2016) through the example of quantitative easing, can generate riskier conditions for investors, potentially leading to the origination of volatility. New markets for financial assets, such as cryptocurrency, are still in their origin and are sensitive to regulations, which can cause spillovers (Pelagidis, Kostika, 2022).

Several authors have highlighted the role of the political environment as one of the antecedents of volatility spillovers. It can moderate the strength and duration of volatility spillovers. (Gungoraydinoglu, Çolak, Öztekin, 2017) identified the political environment as a key driver of a firm's information risk, transaction costs, and leverage across the globe. Consequently, the financial policy regime shapes the intensity and possibility of volatility spillovers. This statement is supported by the example of financial liberalization in the work by (Huo, Ahmed, 2017), whereas (Caporale, Hadj Amor, Rault, 2014) proved that liberalization catalyzes volatility spillovers and, hence, must be implemented carefully in emerging markets.

Other evidence shows that volatility spillovers vary across different geographic regions. The degree of net volatility transmission is influenced by the source of the crisis and the specific market involved (Garcia, Rambaud, 2023). Additionally, the stock markets of emerging countries are more sensitive to global factors such as economic uncertainty and oil price volatility (Syed, Bouri, 2022). Although the determinants partially unveil the mechanisms of volatility spillovers in financial markets, they do not provide a complete explanation. Accordingly, the next part of our literature review will provide more details on international economic relations as a possible cause and effect of volatility spillovers in international financial markets.

2.2. International economic relations in the context of financial markets interconnections

International economic relations contribute to the interconnections of financial markets, affecting stock prices, currency exchange rates, and commodities (Stockman, 1988). The magnitude of spillovers depends on the receiving country's trade and financial integration (Georgiadis, 2016). The mechanisms of spillover transmissions occur through various channels. Tighter economic connections are more likely to cause transmissions of volatilities. Bilateral trade is one such channel. The position of a country as an importer or exporter can also help predict which side of economic relations is more likely to become the source of volatility. For instance, (You et al., 2024) found that the country-importer is a stronger source of spillover than the country-exporter.

Another important characteristic of economic relations is the trade deficit. As shown by (Ma, Cheng, 2005), a trade deficit increases foreign debt, decreases foreign reserves, and weakens confidence in the exchange rate of the domestic currency. These factors can pre-

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text global political and economic events, as demonstrated in the case of the US–China trade war, where China's trade profit was one reason to restrict its trade in American markets (Chatziantoniou, Floros, Gabauer, 2022). Such changes urge companies to find other economic partners as better options for trade. Consequently, peaks in volatility occur during periods of growing economic and financial instability (Morales-Zumaquero, Sosvilla-Rivero, 2018).

Extensive research was dedicated to other aspects of economic ties. (Caporale, Hadj Amor, Rault, 2014) studied the influence of international trade indicators and foreign direct investments. (Agbloyor et al., 2013) indicated the proactive effects of financial development on international trade and manufacturing for the exporting country. (Pan, Fok, Liu, 2007) stated that international trade and exchange rates can have spillover effects on stock market volatility and the interconnectedness of markets. Furthermore, the demand for popular investment targets such as U.S. equities and their substitutes, including corporate bonds, government bonds, commodities, and real estate, can also play a role in influencing stock prices and cause spillover effects in financial markets (Liu et al., 2020).

Economic relations are significant antecedents that cause and transmit volatility spillovers in international financial markets. During times of crisis, their implications become even more evident. The current geopolitical situation acts as a catalyst for volatility. Therefore, we analyze the relations between China and Russia as a dynamic process that explains the quality of volatilities.

2.3. Economic relations between Russia and China

With the high degree of interconnectedness of economies, political and economic events result in volatility spillovers in financial markets, which mean the transmittance of volatility patterns from one market to another (Dedi, Yavas, 2016). Some markets may be more insulated from external shocks due to factors such as strong domestic demand or government policies that limit exposure to external risks (Banerjee, Devereux, Lombardo, 2016). However, it is important to note that even markets that are relatively insulated can still be affected by spillover effects if the shocks are large enough or if they are transmitted through indirect channels (Sugimoto, Matsuki, Yoshida, 2014).

In our study, we concentrate on the dynamics of economic relations and their implications for financial markets. This is why we use the context of China–Russia economic relations. Since 2022, Russian financial markets were detached from global financial institutions, becoming more isolated and locally oriented. Yet, China is one of the few markets that did not join sanction policies and continued to maintain a neutrally friendly relationship with Russia. This allowed China to become Russia's most important trade partner. Its export value to Russia is estimated to be over $7.2 billion in 2022, up from $4.3 billion in 2021[4]. The trade balance is characterized by Russia's surplus (Fig. 1), which accounts for around $16 billion[5].

Moreover, the governments of the two countries increased the proportion of payments conducted in their national currencies to 90%, separating their economic relations from other markets. This contrasts significantly with the results of the trade between Russia and India, another newly emerged partner with whom Russia is trying to develop economic relations. Despite the bilateral trade value of $46.21 billion in 2023, India's export amounted only to $3.14 billion, indicating very uneven interac-

[4] China Customs Statistics Office.

[5] China Customs Statistics Office.

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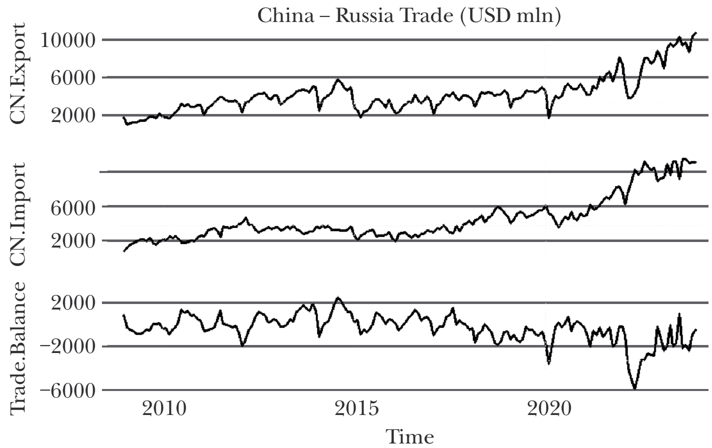

Figure 1.
China–Russia economic relations

Source: Wind Terminal.

tion between the two economies. China's involvement in trade with Russia can have a more significant impact on the financial markets of both economies, supported by the dynamics of their relations (Table 1)[6]. The trade structure also implies that Russia's participation in trade with China contributes significantly to China's manufacturing sector, with its production presumably being sensitive to volatility shocks in the Russian

Table 1.
Economic relations between Russia and China in historical retrospective

Period	Economic relations between Russia and China
2009–2013	The most important drivers of trade between the two countries have been pronounced by the conclusion of strategic agreements on oil and gas export from Russia to China and on bilateral development of Northeastern borderline territories (Larin, 2020). The growth was also supported by the surge in oil prices (Wishnick, 2017)
2014–2016	Despite the outstanding trade outcome in 2014 (Zharikov et al., 2016), trade relationship between Russia and China experienced fluctuations (Larin, 2020). The total trade between the two countries slumped to around $60 billion in 2015 and 2016 due to various factors, including the echoing effects the crisis of 2008 and the aggravation of relations between Russia and Western countries, which furtherly contributed to the expansion of economic ties with China (Figure 1). The negative effects of sanctions had more impact on Chinese export to Russia, while Russian import experienced little negative implications, which can be explained due to its significance as fuel and row resource exporter and the effects of previously established agreements[7]
2017–2020	In the years following 2016, the trade relationship between Russia and China started to recover slowly. The two countries planned to increase bilateral trade to $200 billion by 2023[8]. This period was marked by a steady expansion of economic ties, driven by the development of joint projects in the energy sector, industry, the agricultural sector, and high technology[9]
2021–2023	From 2021 to 2023, the trade relationship continued to strengthen, with the total trade between the countries reaching a record high of about $190 billion in 2022. The trade relationship has become increasingly important, with a qualitative expansion of Chinese–Russian trade in goods and services, driven by the development of joint projects in technology, agricultural and energy sectors (Aksenov et al., 2023). By 2023, the total trade between the countries reached a record high of about $190 billion, with Russia's exports accounting for a large majority of the increase, leading to sharp changes towards its trade surplus[10]

[6] China Customs Statistics Office.

7 WTO. China trade statistics (https://www.wto.org/english/thewto_e/countries_e/china_e.htm).

[8] Russian government. 2023. Mikhail Mishustin meets with President of China Xi Jinping (http://government.ru/en/news/50461/).

[9] WTO. China trade statistics.

[10] WTO. China trade statistics; China Customs Statistics Office.

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energy sector. Additionally, the demand in China's manufacturing sector can drive oil production, transmitting volatility to Russia's main trading commodities in turn. This implies that the structure of trade can influence the patterns of financial spillovers, particularly in emerging market economies (Chambet, Gibson, 2008).

Thus, the trade relations between Russia and China can be characterized as being in a mode of intensification, where Russia's commodity exports are complemented by China's import of higher value-added goods, leading to a mutually beneficial trade partnership and compensating for the negative effects of sanctions on Russia's economy. This can ultimately become the source of positive or negative spillovers in financial markets, especially when one partner economically prevails over the other (Fang et al., 2021).

Recent evidence suggests that trade growth can influence the patterns of financial spillovers, creating long-lasting effects (Bettarelli et al., 2024; Balli et al., 2015). Indeed, the increasing interconnectedness between trade and political relations, combined with the localization of international capital markets, has the potential to reshape the dynamics of financial spillovers. In the case of Russia, its financial markets have become more isolated and locally oriented, with indications that significant events in China's financial markets may have a pronounced impact on Russian stock and commodity prices (Fang et al., 2021).

In our study, we focus on the period from 2009 to 2023 as the start for our chronological analysis to indicate the dynamics of mutual trade development as well as the first wave of global sanctions on Russia's economy that urged its government to look for alternative trade partners, thus increasing the role of China in Russia's economy and indirectly boosting the interconnectedness of their financial markets[11].

3. Data and methods

3.1. Data, sample, and variables

We utilize essential macroeconomic and financial market data as indicators of financial market interconnectedness (Asgharian, Hess, Liu, 2013; Cuñat, Zymek, 2024) to test how the dynamics of China–Russia economic relations influence their financial markets. As previously specified, we define economic relations as the volume of bilateral trade data between Russia and China — specifically, Chinese exports to Russia, Chinese imports from Russia, and the trade balance (You et al., 2024; Ma, Cheng, 2005; Morales-Zumaquero, Sosvilla-Rivero, 2018).

Financial markets in our study are represented by the stock indices of the Shanghai Stock Exchange (SSE) and the Moscow Exchange (IMOEX), as well as government bond yields and financial sector performance indices, namely its price and liquidity. For clarity, we provide the names and descriptions of the variables as they are represented in the analysis in Table 2. The period of the data reflects the years from 2009 to 2023. The frequency of the data is monthly, resulting in a sample consisting of 180 observations in total.

The data are collected from the Wind Information System[12]. Initially, we collected daily data for financial and stock markets; however, due to the unavailability of daily data for macroeconomic indicators, we converted the former into average monthly data. TVP–VAR models do not require variables to be stationary, a cha-

[11] WTO. China trade statistics.

[12] The Wind Financial Terminal is a comprehensive platform that provides financial professionals with access to a wide range of financial data, insights, and analytic tools. It is designed to help users understand China's complex capital markets and economy by integrating market data, fundamental data, research, news, and analytic tools across various asset classes.

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Table 2.
Variable description

Variable	Description
Economic relations indicators	
CN Import	Chinese import from Russia (volume)
CN Export	Chinese export to Russia (volume)
Trade Balance	The balance of trade between China and Russia (volume)
Financial market indicators	
RU Bond Yield	Russian government bonds yield (percentage)
CN Bond Yield	Chinese government bonds yield (percentage)
RU Price	Russian financial sector stock performance (price)
RU Liquidity	Russian financial sector stock performance (volume)
CN Price	Chinese financial sector stock performance (price)
CN Liquidity	Chinese financial sector stock performance (volume)
SSE Volatility	Shanghai Stock Exchange volatility index (percentage)
SSE Price	Shanghai Stock Exchange price index (price)
SSE Returns	Shanghai Stock Exchange return index (percentage)
IMOEX Volatility	Moscow Stock Exchange volatility index (percentage)
IMOEX Price	Moscow Stock Exchange price index (price)
IMOEX Returns	Moscow Stock Exchange return index (percentage)

racteristic that represents a significant advantage in capturing the evolving nature of relationships in economic and financial data. This flexibility enables TVP–VAR models to effectively handle non-stationary behaviors, including time-varying trends and volatility, making them particularly suited for analyzing complex, dynamic systems like international financial markets (Primiceri, 2005; Koop, Korobilis, 2010; Cogley, Sargent, 2005; Nakajima, 2011; Canova, 2007). This adaptability allows the model's parameters to change dynamically in response to shifts in economic and financial conditions, accommodating trends, volatility changes, and other non-stationary behaviors that traditional VAR models might struggle to handle without preprocessing steps like differencing or detrending (Primiceri, 2005; Cogley, Sargent, 2005). The robustness of our findings is further supported by the incorporation of the LASSO method, which refines variable selection and ensures that the most significant predictors are included, thereby enhancing the reliability and interpretability of the results (Foster, Verbyla, Pitchford, 2008).

While the TVP–VAR model inherently accommodates non-stationary variables, we have nonetheless applied log transformations and first differencing to achieve stationarity in our variables. We hypothesize that stationarity is critical for ensuring the robustness and reliability of our empirical results, as it prevents spurious correlations and facilitates the accurate interpretation of dynamic relationships. This approach is particularly important for capturing the evolving financial interconnectedness and volatility spillovers between China and Russia over time, and it enhances data com-

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parability across the studied period, thereby supporting more precise forecasting and meaningful policy implications.

First differencing is employed to stabilize the mean of the series, making the data more suitable for time series analysis, particularly when examining the dynamic relationships between variables. This transformation allows us to focus on changes in the variables rather than their levels, which is crucial for understanding how fluctuations in one economic indicator, such as bond yields or market volatility, influence changes in another (in our study: RU Bond Yield, CN Bond Yield, SSE Volatility, SSE Returns, IMOEX Volatility, IMOEX Returns).

Log transformation, on the other hand, is applied to address the exponential growth patterns often observed in economic and financial time series. By linearizing these series, we simplify the analysis and interpretation of the relationships between variables, particularly in the context of financial market performance, where returns and growth rates are typically multiplicative. This approach is particularly relevant for variables such as CN Import, CN Export, Trade Balance, RU Price, CN Price, SSE Price, IMOEX Price, RU Liquidity, and CN Liquidity (in our study), where stabilizing variance and enabling more meaningful elasticity interpretations are essential for robust analysis.

Regarding this matter, we employ the ADF, Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests to identify stationary variables (Tables 3–4). We decide to rely on the results of KPSS test being the most powerful as compared to the other two tests and providing a more comprehensive view of the data's stationarity properties (according to (Caner, Hansen, 2001; Kwiatkowski et al., 1992; Schwert, 1989)). The KPSS test is particularly sensitive to both stochastic trends,

Table 3.

The results of stationarity tests for the unprocessed data

Variable	KPSS test (p-value)	PP test (p-value)	ADF test (p-value)
CN Import	Non-stationary (0.01)	Non-stationary (0.73)	Non-stationary (0.98)
CN Export	Non-stationary (0.01)	Non-stationary (0.07)	Non-stationary (0.8)
Trade Balance	Non-stationary (0.01)	Stationary (0.01)	Stationary (0.01)
RU Bond Yield	Stationary (0.1)	Non-stationary (0.38)	Non-stationary (0.5)
CN Bond Yield	Non-stationary (0.01)	Non-stationary (0.24)	Non-stationary (0.12)
RU Price	Non-stationary (0.01)	Non-stationary (0.16)	Stationary (0.01)
RU Liquidity	Stationary (0.06)	Stationary (0.01)	Stationary (0.033)
CN Price	Non-stationary (0.01)	Non-stationary (0.098)	Non-stationary (0.2)
CN Liquidity	Non-stationary (0.01)	Stationary (0.01)	Stationary (0.046)
SSE Volatility	Non-stationary (0.01)	Stationary (0.01)	Non-stationary (0.15)
SSE Price	Non-stationary (0.01)	Non-stationary (0.12)	Non-stationary (0.08)
SSE Returns	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
IMOEX Volatility	Non-stationary (0.01)	Stationary (0.01)	Non-stationary (0.18)
IMOEX Price	Non-stationary (0.01)	Non-stationary (0.37)	Non-stationary (0.08)
IMOEX Returns	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)

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Table 4.

The results of stationarity tests after transformation

Variable	KPSS test (p-value)	PP test (p-value)	ADF test (p-value)
CN Import	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
CN Export	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
Trade Balance	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
RU Bond Yield	Stationary (0.1)	Non-stationary (0.38)	Non-stationary (0.5)
CN Bond Yield	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
RU Price	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
RU Liquidity	Stationary (0.06)	Stationary (0.01)	Stationary (0.033)
CN Price	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
CN Liquidity	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
SSE Volatility	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
SSE Price	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
SSE Returns	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
IMOEX Volatility	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
IMOEX Price	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)
IMOEX Returns	Stationary (0.1)	Stationary (0.01)	Stationary (0.01)

which indicate a random walk, and deterministic trends. This dual sensitivity enhances its versatility in detecting various forms of non-stationarity that may not be identified by tests that focus exclusively on the presence of unit roots, such as the ADF and PP tests. By capturing a broader range of non-stationary behaviors, the KPSS test provides a more comprehensive assessment of time series data, ensuring more reliable results in econometric modeling (Kwiatkowski et al., 1992).

The correlation matrix analysis is reported in Figure 2. The results reveal a significant positive correlation between Chinese imports from Russia (CN_IMPORT) and the yield of Russian bonds (RU_BOND_YIELD), as well as between Chinese exports to Russia (CN_EXPORT) and the price performance of the Russian financial market (RU_PRICE). These correlations likely reflect the structure of trade between China and Russia, where imports from China have played a crucial role in Russia's economic activities during the studied period. Additionally, the data suggest a positive correlation between the yields of Russian and Chinese bonds (RU_BOND_YIELD and CN_BOND_YIELD), indicating a potential linkage in their bond markets. However, the analysis shows a lack of significant correlation between stock returns and other indicators, suggesting that returns may be influenced by different factors not captured in this analysis.

Next, we calculate descriptive statistics for the studied data. Table 5 presents the summary statistics of the studied variables. The economic relations indicators demonstrate a significant imbalance in Russia's favor. Several variables exhibit skewness values significantly different from 0, indicating asymmetry in the data distribution. For example, China Import has a skewness of 1.4, while China Export and Trade Balance show negative skewness of −0.7 and −0.3, respectively. Many variables display excess kurtosis (kurtosis − 3) values significantly different from 0, suggesting the data has heavier tails than a normal distribu-

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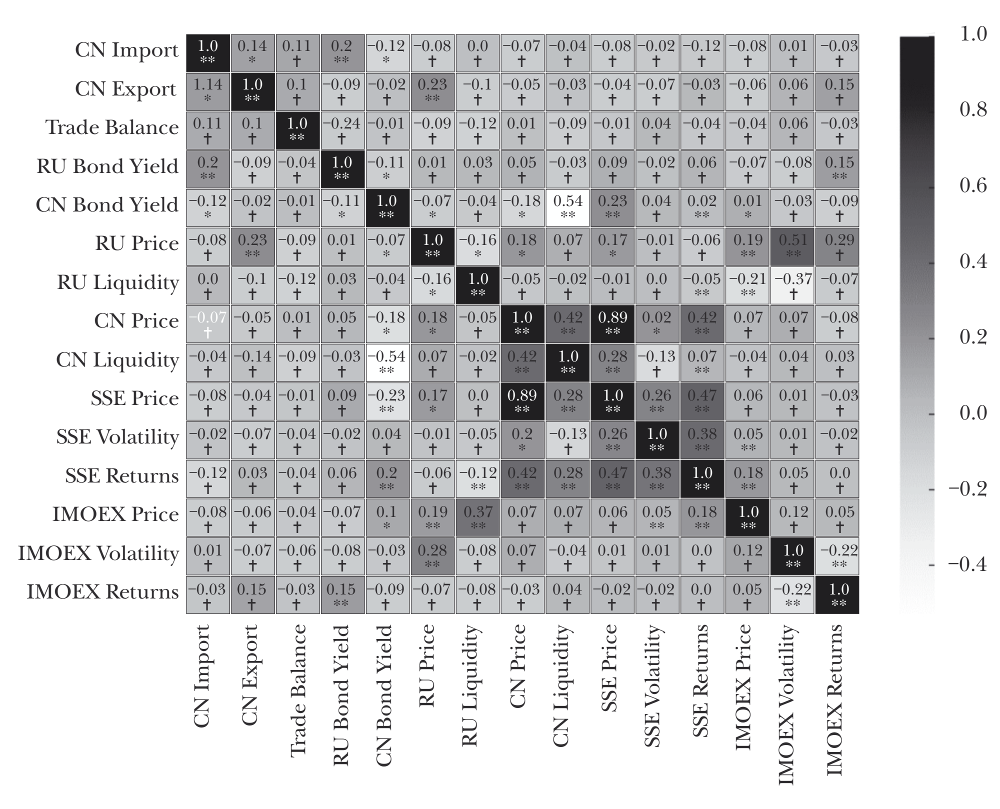

Figure 2.
Correlation matrix with significance levels

Note. * indicates p < 0.05, ** indicates p < 0.01, *** indicates p < 0.001, † indicates not significant.

Table 5.
Summary Statistics

Variable	Mean	Variance	Skewness	Excess Kurtosis	JB	ERS	Q(1)	Q2(1)
CN Import	452999,6	64763151290,5	1,4	1,09	67,8	2,1	1170,7	1072,8
CN Export	5013,1	4908206540,4	−0,7	2,7	73,7	−2,4	46,3	13,9
Trade Balance	−253,7	7067673516,3	−0,3	2,5	51	−6,7	15,9	40,6
RU Bond Yield	8,6	3,4	0,9	0,5	29,9	−0,8	600,8	511,9
CN Bond Yield	−0,003	0,01	0,3	0,9	10	−5,4	34,1	16,3
RU Price	38,2	224596,4	−0,6	6,8	363,8	−4,5	52,7	66,4
RU Liquidity	17407766195,2	6,2	2,3	9,1	793,1	−3,8	229,8	95,2
CN Price	2,6	8510,4	0,8	8,7	594,2	−4,9	30	43,4
CN Liquidity	409,4	1607295355,5	0,8	10,5	852	−8,1	30,7	32,7
SSE Price	4,4	27419,3	−0,4	7,4	421,6	−5,6	25,8	67,8

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Table 5. End

Variable	Mean	Variance	Skewness	Excess Kurtosis	JB	ERS	Q(1)	Q2(1)
SSE Volatility	1070,2	3392359551,7	0,5	3,2	88,08	−2,3	28	72,3
SSE Returns	0	0	−0,6	2,7	67,9	−5,7	12	12,2
IMOEX Price	12,09	13023,9	−1,05	6,2	321,6	−4,5	27,1	47,7
IMOEX Volatility	74111202,6	2,08	−2,02	21,7	3657,6	−3,9	22,5	20,5
IMOEX Returns	0,001	0	−0,001	5,2	207,6	−5,1	25,7	26,6

tion. For instance, Russian Liquidity has an excess kurtosis of 9.1, and IMOEX Returns have an excess kurtosis of 5.2. The JB test statistic (Jarque–Bera test) is large for the most variables, with p-values less than the typical 5% significance level, indicating that the null hypothesis of normality is rejected for these variables.

3.2. The model

To analyze volatility spillovers, researchers need specific econometric methods. The literature highlights that the common econometric methodologies are VAR, GARCH models, and their extensions (Spulbar et al., 2022; Arfaoui, Yousaf, 2022). For instance, the authors (Chen, Mo, Xu, 2022) analyze the interconnectedness and contagion of sectors in China using the CoVaR model. (You et al., 2024) construct a trade–network connecting model using the input–output network approach of (Bilgin, Yilmaz, 2018) to study trade spillovers to stock markets. (Karanasos et al., 2014) employs the GARCH approach for modeling volatility spillovers across commodity metal futures. Other cases include the application of the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model (Kanas, 1998), regressions (Iqbal et al., 2024), and the Granger causality test (Syed, Bouri, 2022).

In this study, to investigate how economy-driven spillovers vary over time, we employ the dynamic connectedness approach and time-varying parameter vector autoregression (TVP–VAR) developed by (Diebold, Yilmaz, 2009, 2012) and later applied in the works by (Balcilar, Gabauer, Umar, 2021; Barunik, Křehlík, 2018). The Dynamic Connectedness Approach involves quantifying the interconnectedness between different variables in a time-varying manner. This approach utilizes techniques like TVP–VAR to capture the evolving relationships among variables over time (Antonakakis, Chatziantoniou, Filis, 2014; Antonakakis, Gabauer, Gupta, 2019). By employing dynamic connectedness analysis, we assess how shocks or changes in one variable propagate and affect others, providing insights into contagion effects, transmission mechanisms, and overall network dynamics within a system (Gabauer, Gupta, 2018; Korobilis, Yilmaz, 2018). Additionally, we employ the LASSO model to check the robustness of the model (Foster, Verbyla, Pitchford, 2008; Shum et al., 2021).

The evolving dynamic connectedness between variables m and n at any given time t within the TVP–VAR model can be mathematically expressed as:

$$D_{mn,t} = \left(1 + \sum_{l=1}^{q} \left|B_{mn,l}(t)\right|\right)^{-1}, \qquad (1)$$

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where, $D_{mn,t}$ signifies the dynamic connectedness between variables m and n at time t, the summation over l captures the cumulative influence of the time-varying coefficients on the connectedness measure, the absolute values of the coefficients, denoted by $\left|B_{mn,l}(t)\right|$ represent the strength of the influence between variables at lag order l. According to dynamic connectedness, the TVP–VAR model can be formulated as:

$$Z_t = \sum_{m=1}^{q} B_m(t) Z_{t-m} + v_t, \tag{2}$$

$$B_m(t) = B_m(t-1) + \theta_m(t), \tag{3}$$

where the vector of variables at time t is denoted by Z_t, time-varying coefficient matrices are represented by $B_m(t)$, the error term at time t is denoted by v_t, and the parameters are updated based on stochastic shocks, represented by noise terms $\theta_m(t)$.

To capture the total and net effects of the studied variables to volatility propagation, we apply such complementary indicators as Total Connectedness Index (TCI), Net Total Directional Connectedness (NET) and Net Pairwise Dynamic Connectedness (NPDC) which are derivatives from TVP–VAR model. TCI captures the overall interconnectedness among variables in the system over time and can be calculated in the following way:

$$TCI = \left(\sum_{i=1}^{N} \sum_{j=1, i \neq j}^{N} \theta_{i,j,t} \Big/ \sum_{i=1}^{N} \sum_{j=1}^{N} \theta_{i,j,t} \right) \times 100, \tag{4}$$

where θ represents the pairwise directional connectedness from variable i to variable j at the moment t. N represents the total number of variables in the system.

NET is the difference between the total directional connectedness to and from a variable, indicating whether it is a net transmitter or receiver of shocks:

$$NET = \sum_{i \neq j} \varphi_{ij} - \sum_{i \neq j} \varphi_{ji}, \tag{5}$$

where φ_{ij} is a series of terms indexed by i, excluding the cases, where i is equal to j and φ_{ji} is a series of terms indexed by j, excluding the cases, where j is equal to i.

NPDC quantifies net influence that one variable has on another over time. Mathematically it can be presented as follows:

$$NPDC_{i,j} = C_{ij} - C_{ji}, \tag{6}$$

where $NPDC_{i,j}$ represents the net pairwise directional connectedness from variable i to variable j; C_{ij} is the total directional connectedness from variable i to variable j and C_{ji} is the total directional connectedness from variable j to variable i.

By integrating these equations with the dynamic connectedness metric, we can thoroughly analyze the evolving relationships and interactions among the variables over time using the TVP–VAR framework. The primary objective of this approach is to capture how economic relationships and their changes over time influence financial markets. Specifically, we aim to understand how shocks in one variable propagate through the system and affect other variables, providing insights into contagion effects, transmission mechanisms, and the overall dynamics of the financial network. To ensure that the data used in this analysis is stationary, we apply necessary transformations such as first-differencing to the non-stationary variables, as identified by preliminary tests like the KPSS test. This preparation allows for more accurate modeling within the TVP–VAR framework. Using this extended model, our analysis focuses on the dynamic and

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evolving financial interconnections between China and Russia, with particular attention to how bilateral trade and economic activities affect their respective financial markets over the period from 2009 to 2023. This comprehensive approach will enable us to provide robust insights into the nature of financial spillovers and the interconnectedness of global markets in the context of significant geopolitical and economic changes.

To ensure the robustness of our findings, we employ the LASSO model (Least Absolute Shrinkage and Selection Operator) for additional verification (Foster, Verbyla, Pitchford, 2008; Shum et al., 2021):

$$\zeta_t = \alpha + \sum_{m=1}^{q} B_m Z_{t-m} + \lambda \sum_{m=1}^{q} \left|\beta_m\right|, \tag{7}$$

where ζ_t denotes the predicted value of the vector of variables at time t; α is the intercept term; β_m represents the coefficients for the lagged values of the variables; Z_{t-m} denotes the vector of variables at lag m; λ is the regularization parameter that controls the degree of shrinkage applied to the coefficients β_m; the term $\sum_{m=1}^{q} \left|\beta_m\right|$ is the L1 norm, which imposes a penalty proportional to the absolute values of the coefficients, encouraging sparsity. According to the last, the LASSO model aims to minimize the residual sum of squares subject to the L1 norm penalty, formulated as:

$$\min_{\alpha,\beta} \left(\sum_{t-1}^{T} \left(Z_t - \alpha - \sum_{m=1}^{q} B_m Z_{t-m} \right)^2 + \lambda \sum_{m=1}^{q} \left|\beta_m\right| \right), \tag{8}$$

where T is the total number of time periods in the dataset.

By implementing the LASSO model, we aim to achieve several key objectives. Firstly, we seek to identify the most significant predictors among the variables, allowing for a more focused and insightful analysis. Secondly, we aim to enhance the prediction accuracy of the dynamic connectedness analysis, ensuring that our results are robust and reliable. Lastly, the LASSO model helps to provide a more interpretable framework by shrinking less important coefficients to zero, thereby simplifying the overall model structure and making it easier to understand and interpret the relationships between variables. This approach not only improves the clarity of the findings but also aids in better decision-making based on the identified key predictors.

4. Empirical results

Our analysis explains trade-driven volatility spillovers, focusing on their temporal dynamics and magnitude. Accordingly, we present Static Connectedness in Table 6. Each cell of the table represents the percentage of forecast error variance in the row variable that is explained by the column variable. The table is explanatory in how often shocks are transmitted between different variables in the TVP–VAR model. The «NET» row shows the net connectedness of each variable, where a positive (negative) value indicates whether a variable is a net shock transmitter (receiver). The "NPT" row shows the count of directional spillovers from one variable to another.

Additionally, we illustrate the dynamic network connectedness (Figure 3) and the total connectedness index (Figure 4) to demonstrate how these coefficients vary over time. The results demonstrate that import is connected to financial and stock indicators, whereas NET coefficient of export is very small and indicates little connection. As shown in Table 6, Chinese imports from Russia exhibit a notable positive relationship with the RU Bond Yield, RU Liquidity, and IMOEX Volatility, suggest-

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ing that changes in these variables are often associated with changes in China's imports. Conversely, China's exports to Russia show a relatively small positive relationship with the RU Price, indicating a smaller share of China's exports in the interconnectedness of the two economies.

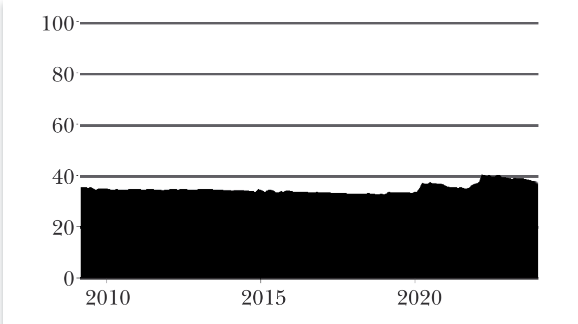

Figure 3.
Dynamic total connectedness index

The time-varying behavior (Figure 3) demonstrates that the strength and direction of the linkages between the variables are not constant but instead evolve in response to changing economic conditions, policy shifts, or other external shocks. This variability reflects significant global events, including the initial sanctions imposed on Russia, the COVID-19 pandemic, and the onset of the conflict in 2022. In 2014 and 2016 there were two small shocks, after which there was a slow, but stable decline in the connectedness between Russian and Chinese markets until 2020. A similar pattern is observed following the shock of 2022, where the index declines. Despite the overall growth in economic relations, the index plot remains relatively flat for most of the studied period, with fluctuations occurring only in response to major global political, social, and economic events, and tends to revert to previous levels. This indicates a generally low level of interconnection between the two financial markets.

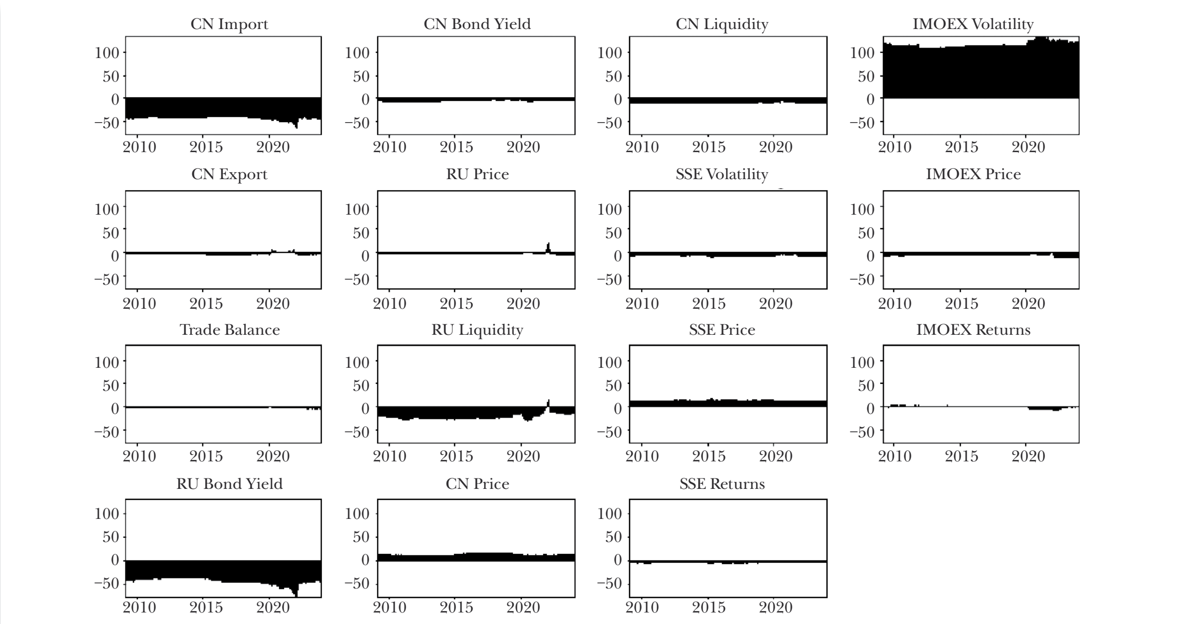

Figure 4.
Net total directional connectedness

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Table 6.

TVP–VAR model coefficients and static connectedness across variables

Variable	CN Import	CN Export	Trade Balance	RU Bond Yield	CN Bond Yield	RU Price	RU Liquidity	CN Price	CN Liquidity	SSE Price	SSE Volatility	SSE Returns	IMOEX Price	IMOEX Volatility	IMOEX Returns
CN Import	38.10	1.1	0.6	14.39	0.28	0.24	14.76	0.43	0.14	0.34	0.13	0.15	0.06	28.22	1.05
CN Export	2.04	86.04	0.79	0.56	0.16	4.29	0.72	0.67	0.4	0.47	0.49	0.11	0.64	0.98	1.64
Trade Balance	1.24	0.85	92.64	0.46	0.1	0.7	0.21	0.19	1.01	0.29	0.17	0.58	0.88	0.49	0.19
RU Bond Yield	9.26	0.49	0.28	26.30	0.19	0.63	20.54	0.82	0.18	0.80	0.15	0.27	0.33	38.14	1.63
CN Bond Yield	0.4	0.16	0.09	0.12	83.58	0.56	0.62	3.08	0.17	4.58	0.19	3.68	0.97	0.24	1.57
RU Price	0.15	3.85	0.58	1.43	0.52	77.28	0.74	2.14	0.21	2.09	0.09	0.49	2.27	2.02	7.85
RU Liquidity	2.85	0.55	0.26	4.9	0.25	0.28	30.41	0.92	0.27	0.69	0.2	0.15	0.19	56.06	2.02
CN Price	0.02	0.33	0.09	0.42	1.61	1.22	0.79	43.05	8.08	34.59	1.87	7.47	0.19	0.19	0.09
CN Liquidity	0.06	0.36	0.81	0.09	0.15	0.21	0.28	13.99	74.74	6.88	0.83	0.28	0.19	1.04	0.09
SSE Price	0.04	0.23	0.29	0.8	4.58	1.18	1.22	34.4	3.95	42.81	2.98	9.72	0.14	0.09	0.07
SSE Volatility	0.05	0.45	0.17	0.15	0.19	0.09	0.2	3.29	0.85	5.27	76.45	12.35	0.21	0.34	0.09
SSE Returns	0.15	0.08	0.58	0.27	3.68	0.37	0.82	10.34	0.23	13.52	9.65	59.58	1.39	0.29	0.07
IMOEX Price	0.07	0.63	0.88	0.33	0.97	2.47	3.96	0.36	0.19	0.27	0.23	1.9	84.16	2.02	0.87
IMOEX Volatility	3.33	0.94	0.49	38.14	0.24	0.28	2.93	0.27	0.17	0.06	0.15	0.17	1.65	81.98	2.82
IMOEX Returns	0.39	1.55	0.19	1.63	1.57	8.07	0.73	0.19	0.07	0.14	0.1	0.08	0.85	4.99	79.84
NET	−41.86	−2.38	−1.92	−42.96	−5.34	−2.12	−21.07	14.14	−9.33	12.81	−6.35	−3.01	−5.87	115.37	−0.1
NPT	5	2	1	6	3	8	10	13	7	12	7	8	2	13	8

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Next, we analyze the individual weight of each variable as a volatility transmitter using their net total directional connectedness (Figure 4) to gain a more comprehensive view of the factors causing volatility spillovers in the two markets. Our analysis reveals that volatility on the IMOEX exchange, and prices on Chinese financial sector together with SSE prices are net transmitters of volatility, with IMOEX volatility having the greatest impact. Contrary to our initial research assumption, which suggested that economic relation indicators might cause volatility in financial markets, we observe that economic relations are recipients of overall financial market shocks. Also, the yields of Russian bonds indicate reception of a lot of impact.

A more detailed view is obtained from the analysis of dynamic pairwise connectedness, as represented in Figure 5 and Figure 6, which illustrate how variables directly affect each other. Specifically, the following observations are made: the economic relations indicators emerge as the receivers of shocks from financial markets with Chinese import being much more affected than Chinese export. IMOEX Volatility, RU Liquidity and RU Bond Yield are the main shock contributors. In contrast, Chinese exports to Russia show minimal influence either as transmitter or receiver of shocks in financial markets, indicating a limited impact of the exports of Chinese goods to Russia. However, we observe that since 2020 Chinese exports start affecting RU Liquidity.

We detect that stock returns in both markets remain nearly unaffected, — a phenomenon that deserves further explanation. However, overall, Russia's trade and financial markets are the main sources of volatility for China's financial markets.

To assess the robustness of the model and address potential issues caused by the high number of variables, we employed the LASSO model (Gabauer et al., 2020), as shown in Table 7. The LASSO model indicates that all model coefficients are not equal to zero, representing their significance (Leng, Lin, Wahba, 2006).

Starting with SSE Volatility, it exerts a moderate yet significant negative effect on NET, with a coefficient of −520.375, and a more pronounced positive impact on NPT, registering a coefficient of 13.00. This suggests that while volatility in the SSE market influences both NET and NPT, the latter is more sensitive to these fluctuations. For IMOEX Volatility, coefficients of 1.59 for NET and 8.00 for NPT

Table 7.

The LASSO model coefficients

Variable	NET	NPT
SSE Volatility	−52.30	1.00
IMOEX Volatility	64.69	2.00
China Export	−2.30	11.00
China Import	−0.41	6.00
Trade Balance	9.37	5.00
RU Price	56.97	9.00
RU Liquidity	−66.49	8.00
CN Price	36.21	14.00
CN Liquidity	17.62	10.00
IMOEX Price	−69.97	5.00
IMOEX Returns	9.16	6.00
SSE Price	29.66	12.00
SSE Returns	−21.70	7.00
RU Bond Yield	−6.64	4.00
CN Bond Yield	3.86	5.00

Notes. Positive coefficients indicate a direct relationship with the response variable, while negative coefficients suggest an inverse relationship. Coefficients with large magnitudes reflect a strong influence of those variables on the model's outcome. No coefficients are zero, indicating that the LASSO model did not remove any variables. This suggests that all variables are contributing to some extent.

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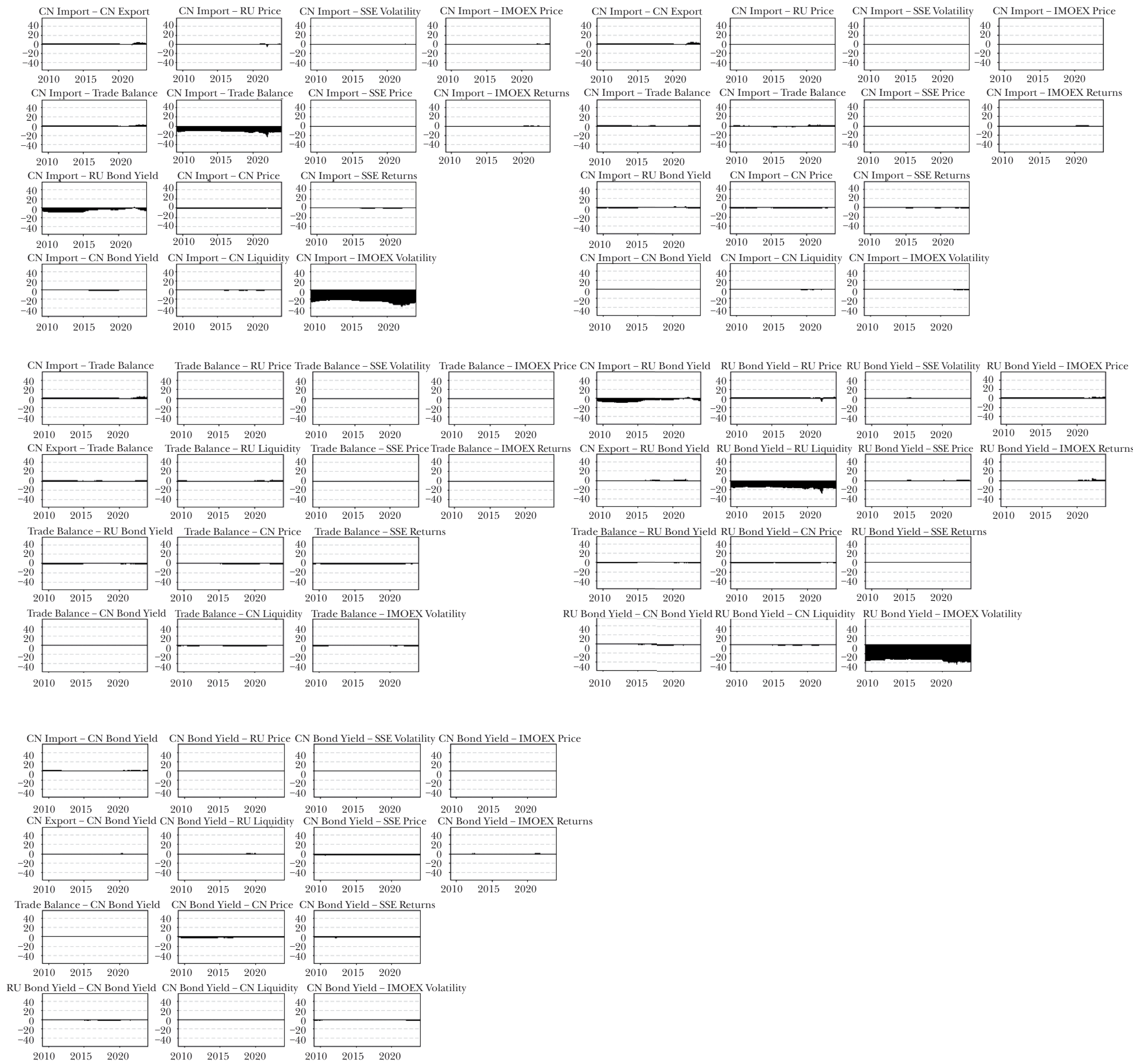

Figure 5.

Dynamic pairwise connectedness

indicate a positive relationship with both variables, implying that increased volatility in the IMOEX market elevates both NET and NPT, with a sharper rise in NPT.

Chinese exports have a dual effect: a negative coefficient of −1.78 for NET suggests a reduction in NET with higher exports, while a positive coefficient of 6.00 for NPT highlights a beneficial impact, reflecting the complex dynamics of China's export activity. Similarly, Chinese imports show coefficients of −4.35 for NET and 3.00 for NPT,

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Figure 6.
Dynamic Pairwise Connectedness (continued)

indicating that while increased imports negatively influence NET, they positively affect NPT, underscoring the varied sensitivity of these indicators to China's trade behavior.

The Trade Balance stands out with positive coefficients of 10.03 for NET and 6.00 for NPT, suggesting that a higher trade balance benefits both variables, particularly NET. In contrast, RU Price exhibits a negative effect on NET (coefficient of −4.27) and a positive effect on NPT (coefficient of 6.00), indicating differing responses to price changes in the Russian market. SSE Price and SSE Returns also show divergent impacts: negative

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effects on NET (–3.84 and –1.54, respectively) and significant positive effects on NPT (10.00 and 8.00, respectively), reflecting different sensitivities to market changes.

RU Bond Yield has a strong negative impact on NET (–10.38) and no significant effect on NPT (0.00), highlighting NET's vulnerability to Russian bond yields. Similarly, CN Bond Yield shows a negative influence on NET (–5.24) and a slight positive impact on NPT (1.00). RU Liquidity positively affects both NET and NPT (coefficients of 1.10 and 8.00, respectively), with a stronger influence on NPT, emphasizing the importance of liquidity in the Russian market.

CN Price demonstrates substantial positive effects on both NET (17.17) and NPT (14.00), underscoring the critical role of Chinese market prices. CN Liquidity, with coefficients of 0.70 for NET and 10.00 for NPT, benefits both variables, particularly NPT. Finally, IMOEX Price and Returns reveal nuanced effects: a negative impact on NET (–1.16) and a positive impact on NPT (9.00 and 3.00, respectively), indicating that price and return changes in the IMOEX market are perceived differently by NET and NPT, with NPT generally experiencing stronger effects.

5. Discussion

Financial markets most affected by bilateral economic activities are those with extensive financial linkages between countries (Agénor, Pereira da Silva, 2022). This suggests that larger spillovers occur between countries with significant portfolio exposures to financial shocks. Additionally, real economic linkages through bilateral trade deepen financial relations between countries, making them more vulnerable to income shocks that can impact asset returns. Geographical preferences in portfolio investment, such as international diversification, also influence financial spillovers (Dedi, Yavas, 2016). Countries with diversified portfolios are less susceptible to spillovers compared to those with concentrated investments. Therefore, financial markets with strong portfolio investment ties, deep bilateral trade relationships, and diversified geographical investments are particularly impacted by bilateral economic activities (Rehman, Shah, 2016). Over the last decade, economic relations between China and Russia have shown significant growth. The imposition of sanctions on Russia indicates that both sides will place more importance on the development of these relations. Hence, as reflected in our research question, we initially assumed that, given unprecedented economic and political events, the linkages between the two markets would strengthen.

The data analysis confirmed this assumption. Overall connectedness between the financial markets of both countries has increased. However, the quality of this connection is bumpy. Russian financial markets are the main sources of volatility for Chinese markets. This factor notably impacts on a wide range of financial market and economic relations indicators, especially Chinese imports from Russia. In contrast, Chinese exports to Russia show minimal influence on financial markets. These findings highlight the asymmetry in the influence of economic relations indicators on financial markets, with Russian exports to China playing a substantial role in receiving the shocks. This complements the previously established conclusion by (You et al., 2024) that importers have greater influence on financial markets than exporters. The enactment of sanctions resulted in global inflation (Korosteleva, 2022); however, Russia's position as China's trade partner mitigates the impact of this volatility, which is reflected in the moderate TCI coefficients.

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An interesting observation in our analysis is the lack of shock reception for equity returns during significant global events. This is contrary to the conventional assumption that returns are volatility-sensitive for energy-exporting countries (Liu et al., 2022). We propose three explanations for this phenomenon. First, geopolitical or regulatory factors may have isolated the Russian market, limiting its direct exposure to foreign economic relations and financial markets (Yahya et al., 2021). Second, market inefficiency may play a role; sanctions and the shift to more locally oriented markets in Russia might insulate domestic stock returns from external shocks (Lansing, LeRoy, Ma, 2022). Domestic investors may be focusing on sectors less influenced by international economic relations, effectively diversifying away the impact of external volatility. Third, actions by Russia's government or central bank may have insulated domestic stock markets from international shocks (Fang, Shao, 2022).

The results of our study align with findings in the existing literature. For example, the observation that Russian exports to China are significantly affected by Russian and Chinese financial markets adds to the findings of (You et al., 2024), who highlight the substantial impact of importers on financial markets. Furthermore, the study's evidence that financial market interconnectedness can be asymmetric, with one country (in this case, Russia) exerting more influence, supports previous research by (Rehman, Shah, 2016) on the importance of strong portfolio investment ties and bilateral trade relationships in driving financial market dynamics. However, our study also presents findings that diverge from established literature. The limited impact of Chinese exports on Russian financial markets contrasts with the general expectation of reciprocal financial interconnectedness in bilateral trade relations. This discrepancy may be attributed to the unique geopolitical and economic circumstances surrounding China–Russia relations, particularly the imposition of global sanctions on Russia. Additionally, the lack of significant volatility spillovers to equity returns during major global events challenges the conventional view that energy-exporting countries are more susceptible to volatility (Liu et al., 2022).

The results of our study have the following practical relevance for investors. Understanding the specific mechanisms through which bilateral trade between China and Russia impacts financial markets can help managers design more effective hedging strategies to mitigate risks associated with geopolitical and economic uncertainties. Additionally, the study highlights the importance of diversification in investment portfolios. Managers need to consider the influence of bilateral trade relations on market volatility and adjust their asset allocations accordingly. Diversifying investments across different asset classes, including stocks, bonds, and commodities, can help reduce exposure to market-specific risks. By recognizing the significant predictors of market volatility, managers can make more informed decisions. The use of advanced econometric models such as TVP–VAR and LASSO provides a nuanced understanding of how shocks in one variable propagate through the financial system, enabling managers to anticipate and respond to potential market disruptions more effectively. Moreover, the findings suggest that strategic trade partnerships, such as those between China and Russia, play a crucial role in influencing financial markets. Managers will benefit from leveraging these insights to strengthen their international trade relationships and explore new markets that can provide stability and growth opportunities amidst global economic shifts.

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Our study also offers important implications for policymakers, particularly those focused on economic stability, trade policies, and financial market regulation. By considering the impact of bilateral trade relations on financial market stability, policymakers can develop more resilient trade policies. The study's insights into how trade structures and economic dependencies influence market volatility can inform the development of policies that promote balanced and resilient trade relationships. Furthermore, the findings underscore the need for robust financial market regulations that can mitigate the adverse effects of volatility spillovers. Policymakers need to ensure that regulatory frameworks are adaptable to the dynamic nature of market interconnections and can effectively manage systemic risks arising from international trade relations. Given the identified influence of monetary policies on financial market volatility, central banks should consider incorporating these insights into their policy adjustments. Understanding the time-varying impacts of trade relations on market dynamics can help central banks design more targeted and effective monetary interventions. Additionally, policymakers need to be aware of the geopolitical risks that influence bilateral trade and financial markets. The study highlights the significance of maintaining stable and cooperative international relations to minimize market disruptions. Policymakers ought to prioritize the fostering of diplomatic and economic ties as a means of mitigating geopolitical tensions and enhancing global financial stability. Concurrently, promoting economic diversification represents a critical strategy for reducing systemic vulnerability to external shocks. This involves supporting sectors that are less exposed to international trade fluctuations and promoting innovation and development in domestic industries. Diversification can enhance economic resilience and reduce dependency on a limited number of trade partners.

6. Conclusions, limitations, and suggestions for future work

Although the unprecedented rise of China as Russia's leading economic and geopolitical partner, our analysis concludes that this partnership has a moderate effect on the magnitude of volatility spillovers. Like the findings of by (Wang et al., 2023), this can be attributed to uncertainty in global financial markets, Russia's isolation from them, and the slow adaptation of investors to changes in the global economic and political landscape (He, 2022). From a theoretical perspective, we contribute to the research on volatility spillovers by analyzing the influence of international economic relations on financial markets during the times of uncertainty. This is particularly relevant given the growing significance of China–Russia political and economic relations. Our study also enriches the existing discussion on market efficiency by examining the dynamic effects of the increasing interconnection between the Chinese and Russian economies, shedding light on the role of international economic relations in shaping financial market outcomes.

Our study is not without limitations. There are additional factors in economic relations that require analysis, including commodity exchange data, foreign direct investment (FDI) data, and mergers and acquisitions (M&A) transactions. We suggest considering these factors in future studies as they are critical determinants for investors' decisions. Another limitation of this paper, driven by the necessity to include indicators of economic relations, is the monthly frequency of the data. We believe that narrowing the data frequency to daily could help to capture more information and provide additional insights, though this depends on the factors used for analysis.

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Финансовая взаимосвязь российского и китайского рынков: динамическая оценка

Аннотация. Исследование посвящено оценке динамической взаимосвязи и побочных эффектов волатильности на финансовых рынках Китая и России в период с 2009 по 2023 г. Особое внимание уделено их экономическому и финансовому рыночному взаимодействию. Используя модель векторной авторегрессии с изменяющимися во времени параметрами (TVP–VAR) и модель LASSO, мы изучаем, как двусторонние торговые отношения взаимосвязаны с такими различными параметрами финансовых рынков, как биржевые индексы, доходность облигаций и показатели ликвидности. В результате выявлена значительная положительная корреляция между китайским экспортом в Россию и функционированием российского финансового рынка, что подчеркивает важность внешней торговли. Результаты исследования показали, что экономические отношения между Китаем и Россией существенно влияют на финансовые рынки обеих стран, что обусловлено геополитической и экономической ситуацией. Результаты исследования усиливают понимание международных экономических отношений и динамики финансовых рынков через такие их аспекты, как волатильность и экономическая взаимосвязь.

Ключевые слова: *побочные эффекты волатильности; российский и китайский финансовые рынки; российско-китайские экономические отношения; модель динамической векторной авторегрессии.*

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