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Linkages between the Chinese stock market and the macroeconomic climate in the U.S. and EU

A VAR ANALYSIS

Master Thesis

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The purpose of this paper is to examine the relationship between investments in the Chinese stock market and shocks to the macroeconomic climate in the U.S. and in the EU. Four different indices are used in determining the investment response to shocks in the two different geographical regions of interest – The Shanghai Composite Index, CSI 300 Information Technology Index, CSI 300 Materials Index, and CSI 300 Industrials Index – with the first being a broader index and the three latter being a sector-specific index. Each index is investigated in relation to imports, central bank short-term interest rate, industrial production, and inflation, for both the U.S. and EU using vector autoregressive (VAR) methods such as causality, variance decomposition, and impulse response functions. The results suggest that out of the four variables, import and inflation are the most significant variables in terms of their transmissive effects on the Chinese stock markets. The effect of the central bank rates and industrial production are significantly smaller and cannot be claimed to explain Chinese stock variations, at least in the context of this model and data set. This paper provides insights for investors looking to invest in the Chinese stock market and for policymakers operating within a Chinese context.

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1. INTRODUCTION

In the last couple of decades, globalization has brought the economies of the world closer together. The interdependence between countries, companies, and consumers has given rise to increasingly complex international value chains and trade relationships (Collier, 2017). In 1970, a mere 26,7 % of world GDP was generated through cross-border trade. In 2016 that figure had reached 56,2 % (World Bank, 2017).

In the area of international finance, globalization has facilitated a closer integration between national financial markets. A development that has both created risks and rewards. Investors have seen their opportunities expand by the opening of markets for foreign investment. At the same time, closer financial integration also raises risks of financial contagion effects where a crisis in one financial market might spread rapidly to others. This fear was underscored by the eruption of the Great Recession in 2008 that spread from one market to the next, leaving virtually no economy unaffected (Yongding, 2010).

The crisis intensified academic debate on how deep economic integration between countries truly go and what can be done to reap the benefits without being subject to its woes. The degree of economic integration between the world's largest economies is critical in assessing the potential for contagion effects in the world's financial markets. Grasping the reaction to macroeconomic shocks is necessary to understand the link between financial market volatility and events unfolding in the real economy. Together China, the United States, and the European Union account for over 49 % of the world's total GDP, making the issue of their interdependence key in determining the likely consequences of an economic shock across world markets (Yongding, 2010).

China was late in developing a functioning financial market which has made the country somewhat of a special case in the finance literature. Now, however, the country is home to the world's second-biggest stock exchange in terms of market capitalization and the interest in understanding China's role in the financial markets is growing. In the crisis of 2008, China took a hit as its growth figure fell from 13 % in the last quarter of 2007 to 6,8 % in the same period in 2008. In the same year, the government launched a 4 trillion-yuan stimulus package and the central bank cut interest rates to keep the world recession at bay. This led to a swift

recovery in the following year. The sizeable shock but also the swift recovery raised the issue of how sensitive China truly is to shocks and financial turbulence originating in the U.S. or elsewhere (Yongding, 2010).

The economic and financial ties between China and the U.S. have grown stronger in recent years, but, despite this, there is still limited research into the economic linkages between the two countries in international finance. Most of the available research is primarily focused on national financial markets and on China alone. For instance, Jin (2003) focuses on the linkages between trade and the Chinese currency while Xu (2000) and Zhang (2001) investigates the exchange rate regime and policy-making surrounding the Yuan.

Others, such as Lu and Zhang (2003) focus on the relationship between China's inflation and the Yuan. Hurley (2009) investigates the macroeconomic linkages between the two countries but do not touch the area of how the macroeconomic climate affects investments in the stock market. Wang (2014) and Valukonis (2013) both investigate fluctuations in the investments in Chinese companies on the stock market, but the analysis is limited to using the Chinese macroeconomic climate as the determinant for explaining the investment patterns. Goh, Jiang, Tu, and Wang (2012) constitute one of few studies that combine U.S. macroeconomic variable and the subsequent reaction to shocks on the Chinese stock market. While the U.S. is the biggest importer of Chinese goods, EU is Chinas biggest trading partner overall (China Statistical Yearbook, 2017). Despite this, research investigating linkages between EU and China within finance is even more limited than for the U.S.

The goal of this paper is to investigate the relationship between investments in the Chinese stock market and shocks to the macroeconomic climate in the U.S. and in the EU. Four different indices will be used in determining the investment response to shocks in the two different geographical regions of interest – The Shanghai Composite Index, CSI 300 Information Technology Index, CSI 300 Materials Index, and CSI 300 Industrials Index – with the first being a broader index and the three latter being a sector-specific index. Each index will be investigated in relation to imports, central bank short-term interest rates, industrial production and inflation, for both the U.S. and EU using vector autoregressive (VAR) methods such as causality, variance decomposition, and impulse response functions. Of special interest is the response of each index to shocks in the macroeconomic variables for both regions. This paper provides insights important for investors looking to invest in the

Chinese stock market and for policymakers in determining which trading partner exert the biggest risk factor in case of a macroeconomic shock.

The paper consists of five sections. Section one provides a brief background on the topic at hand as well as an insight into the purpose of this paper. Section two provides a literature review examining previous research in international finance and linkages between the U.S. and China as well as EU and China. This is followed by an empirical section where the methods and results of the linkages between the variables in the models are presented. Section four provides a deeper analysis of the findings in section three and discuss them in relation to previous research. Section five concludes the paper and discusses potential topics of further research within the scope of this paper.

2. LITERATURE REVIEW

2.1 THE ARBITRAGE PRICING THEORY

The identification of the relationship between macroeconomic variables and stock returns has been attributed to Ross (1976) and his formulation of the Arbitrage Pricing Theory (APT). The APT suggests that the return of an asset can be predicted by the linear relationship between the assets expected return and fundamental macroeconomic variables that affect the risk-level of the asset. The theory assumes that markets have tendencies of inefficiency resulting in the mispricing of assets where some are undervalued, and others are overvalued (Ross, 1976).

In due time, markets will correct the price of the asset, but the time-lag offers a window of opportunity for investors to take advantage of the differences between expected returns and the real returns through arbitrage. The theory is considered as an alternative to the simpler but less adjustable capital asset pricing model (CAPM) that considers the more general market-risk to be the central factor in explaining stock returns (Ross, 1976). Ross's (1976) original article was limited by the lack of empirical evidence suggesting which macroeconomic factors play a role in explaining returns (Narayan & Narayan, 2012). In Roll and Ross (1980) an attempt was made to correct for this shortcoming by conducting empirical tests to identify the relevant macroeconomic variables. The study proposed four macroeconomic variables which

all played a significant part in explaining asset returns, namely - inflation, industrial production, interest rates and risk premiums (Roll & Ross, 1980).

With the growth of the APT literature the range of macroeconomic variables that potentially help explain returns have expanded considerably. Factors such as dividends, exchange rates, trade, GDP, crude oil price, P/E-ratio, stock variance and book-to-market ratio constitutes just a few examples of factors that researchers have added to the original four proposed by Roll and Ross (1980). Early research into the link between returns and macroeconomic variables centered around the domestic linkages, where homegrown shocks in macroeconomic variables were assumed to have a deeper effect on a single country's stock returns than shocks originating from abroad (Narayan & Narayan, 2012).

Fama (1981) is one example of an influential article in this specific field of study that focused on explaining the negative correlation between inflation and stock returns in the U.S. that had puzzled researchers because investing in stocks had traditionally been viewed as a viable hedge against the woe of inflation (Fama, 1981). Fama (1981) suggested that this could be explained by the fact that stock returns and their variation were caused by changes in macroeconomic variables. Stock markets functioned as a proxy for booms and busts in the real economy. As output grew, so did stock returns, while inflation tended to be negatively correlated to output booms and productivity gains (Fama, 1981).

Chen, Roll and Ross (1986) expanded on the four original factors proposed by Roll and Ross (1980) by including growth in oil prices, per capita consumption and return on the NYSE index. However, the results didn't show significance for the newly introduced variables whilst retaining the significance of Roll and Ross's (1980) original variables. Especially industrial production showed a noticeable tendency to predict stock returns (Chen, Roll & Ross, 1986).

Studies on the effect of domestic economic variables on asset returns remain the most common, in recent years there has been a rise in the number of studies conducted using macroeconomic variables of one country to predict asset returns in another country (Narayan, Narayan, 2012). Becker, Finnerty, and Kopecky (1995) broke new ground with a study that tracked the reaction of both U.S. and foreign bond futures prices to variation in U.S macroeconomic variables. Nikkinen and Sahlstrom (2004) used both domestic and U.S macroeconomic news to predict stock volatility in the Finnish and German stock market but found no significant effect from either domestic or U.S. news releases.

Nasseh and Strauss (2000) used variance decomposition and Johansen's cointegration test to identify a long-run relationship between stock prices and macroeconomic activity in six European countries, Germany, Italy, France, Switzerland, Netherlands and the United Kingdom. The motivation to pick the six specific countries included in the study was founded on the conviction that the more integrated two economics are, the more integrated should the two capital markets be (Nasseh & Strauss 2000).

This, in turn, leads to the conclusion that shocks in one country's macroeconomic fundamentals should lead to subsequent shocks in the other country's stock returns, as the results of the study also indicated. In this context, the degree to which foreign shocks in macroeconomic activity can predict domestic stock returns provides a measurement of the level of economic integration between two economies (Nasseh & Strauss, 2000).

2.2 APT AND THE INTEGRATION OF FINANCIAL MARKETS

The evolution of APT towards using foreign macroeconomic variables to explain domestic returns is closely linked to the development and furthered integration of global capital markets that was especially prevalent in the late 1980s and 1990s. Through trade, increased productivity and technological progress the economies of the world have become ever more integrated in the last couple of decades. The financial markets are no exception to this rule (Agènor, 2003).

The development of new financial instruments, the IT-revolution, deregulation and the fall of communism have all contributed to financial integration between countries, markets and firms (Chevallier, Nguyen, Siverskog &Uddin, 2017). The growth of international financial markets has created far-reaching opportunities for investors in search of higher returns and viable assets to diversify their portfolios (Agènor, 2003).

However, the financial integration also strengthens tendencies for stock markets to converge, potentially leading to increased difficulties to hedge to avoid risk. With non-convergent markets, institutional investors could hedge against losses in developed markets by investing in emerging markets and vice versa. With lower levels of financial integration emerging markets respond more to regional and local shocks rather than global, making diversification possible. It is this tendency towards convergence that produces the necessary prerequisites for the APT to function beyond domestic markets and be applied in an international setting (Narayan & Narayan, 2012).

The effect of financial integration in developing countries is a growing field of study with diverging views on the pros and cons of increased financial integration. Edwards (2001) found that international financial integration increased growth in emerging economies but hampered growth in rich countries. Arteta, Eichengreen, and Wyplosz (2001) argue that Edwards findings are sensitive to small adjustment to the econometric model, leading to questions of the reliability of the results (Edison, Levine, Ricci & Sløk, 2002).

In the neo-classical growth model, increased financial integration provides capital to poor countries lacking sufficient capital resources, thus generating positive productivity effects. The resulting increase in competition leads to higher growth and more efficient domestic financial systems (Edison et. al., 2002). Other scholars have emphasized the tendency of financial innovation and integration to increase inequality in emerging economies by providing financial services to affluent individuals that the poor cannot access as readily (Law, Tan & Azman-Saini, 2014).

Boyd and Smith (1992) argue that financial integration risks hampering growth in developing economies with weak institutions and dysfunctional justice systems. The inherent weakness in the institutions can produce severe capital outflows from the dysfunctional countries to developed countries with stronger institutions as capital controls are loosened and financial integration progresses. This suggests that increased financial integration promotes growth in countries that are already rich and have strong institutions while weakening the capital-allocation in developing countries (Boyd & Smith, 1992).

Many transition economies in Eastern Europe, Latin American and East Asia have moved towards financial integration and liberalization by removing capital controls, allowing Foreign Direct Investment (FDI), adopting a more free-floating currency regime and deregulating the domestic financial markets. In the immediate aftermath of these policy changes, the countries saw a surge in inflows of private foreign capital. As the policy reforms progressed the inflows reached even higher levels in the 1990s (Agènor, 2003).

However, the loosening of controls and increased openness faced a backlash in the late 1990s with several financial crises in Asia 1997, Russia 1998, Brazil 1999, Turkey in 2001 and Argentina in 2002. Some scholars saw the turbulence as evidence of how financial openness created the risk of speedy and harmful reversals of capital flows once uncertainty about the stability of economic fundamentals had taken root. Others found the cause in weak macroeconomic discipline rather than an abundance of financial integration (Agènor, 2003).

The debate among scholars is on-going and even though there's a tendency to highlight the benefits of financial integration over the costs there's still a deep divide between many economists on this topic. With the eruption of the financial crisis of 2008, the issue was brought to the center of debate since the crisis showed signs of the emergence of a domino-effect, where convergence between financial markets would lead to volatility spreading from one country to the next, eventually engulfing the entire world's financial system. Still, no strong consensus seems to have been reached on whether the world has had too much financial integration, too little or just enough (Agènor, 2003).

2.3 THE EVOLUTION OF CHINA'S FINANCIAL MARKET

China is a country of particular interest when studying the financial integration of transition economies. Under Mao, the country had only one bank that managed the entire financial system. No stock market existed, and the financial system was, just as the rest of the economy, fully under the state's control. In its transformation from communism towards a "socialist-market economy: Chinese style", as the new economic system has been dubbed in China, the Chinese government implemented several reforms and new regulations to improve the nation's financial system (Carpenter & Whitelaw, 2017).

In their efforts to develop a market economy the government emphasized a form of gradualism with distinct Chinese characteristics, called "crossing the river by touching the stones" where reforms were initiated in an experimental setting, limited in scope and depth. Policy changes deemed unsuccessful where scrapped while successful ones were allowed to spread to other areas of the economy (Brunnermeier, Sockin & Xiong, 2017). This approach differed significantly from many developing countries, particularly in Eastern Europe, that followed a "big bang" approach where rapid privatizations and dismantling of the former communist system was forced through with poor or mixed results (Feltenstein & Nsouli, 2003).

Even though China's gradual reforms took a longer time to apply it is largely hailed as a successful case of market reform. It has also opened the door to a debate on whether gradualism is the preferred method over more sweeping changes proposed by supporters of the big bang approach. Arguments have been put forth suggesting that the success was not due to gradualism itself but rather due to China's emphasis on strengthening competition rather than privatization as its Eastern European counterparts. Whatever the merits of this

argument, it remains largely accepted that China's market reforms have been successful, if yet far from complete (Feltenstein & Nsouli, 2003).

Under Deng Xiaoping, the number of Chinese state banks increased from one state bank to four commercial state banks. In 1985 new banking laws were enacted to strengthen competition between the commercial state banks. In 1990 the first stock exchanges opened in Shanghai and Shenzhen with the main purpose of facilitating the privatization of state-owned assets. This was followed up by the creation of three policy banks in 1994. In the same year, the government launched a new Central Bank law aimed at increasing the independence of the Central bank. The Chinese government also opened to foreign investors and loosened capital and currency controls to improve the investment climate. Despite these liberalizations, much of the stock market remained heavily restricted. The increased openness didn't mean the Chinese government relinquished control altogether. The state remains the central economic authority and holds a de-facto veto in most major areas of the economy, including the financial sector. The government used a system of different categories of shares to control trading and ownership of stock listed companies (Feltenstein & Nsouli, 2003).

State shares are held by a representative of the state and are non-tradable entities. Legal-person shares are also non-tradable but are held by a legal person such as a private institutional investor or a state-owned enterprise (SOE). A-shares are tradable and held by domestic investors and private institutional investors. The government maintains a strict ownership policy to disavow company takeovers. One single investor cannot hold more than 0,5% of the total number of A-shares (Feltenstein & Nsouli, 2003).

B-shares can be held by domestic investors and foreign investors with no limit on ownership. Like A-shares it is traded on the Shanghai and Shenzhen stock exchanges but traded in Hongkong and U.S. dollars. H-shares are shares of companies based in Mainland China but traded on the Hongkong stock exchange with access for both domestic and foreign investors (Feltenstein & Nsouli, 2003).

By using multiple categories and ownership restrictions the state managed to control, directly or indirectly, many of the publicly listed companies. In 2005 only one-third of equity shares were tradable, while the rest remained under state control or supervision. The government intervened frequently in the market by using circuit breakers to steer the value of different assets in the desired direction or halt when favored assets were plummeting. The stock market was plagued by numerous scandals at the time that revealed a casino-like enterprise with state

officials intervening on behalf of favored investors. The financial market was largely segmented from the global financial system and few things functioned in a way expected from experiences of stock market behavior in North America or Europe (Carpenter & Whitelaw, 2017).

Today, however, the situation is somewhat different. The government interventions have decreased significantly, and promises have been made to end the practice altogether. China's stock market has grown more than five-fold to over 7 trillion U.S dollars in 2017, making it the second largest in the world, measured in market capitalization (Carpenter & Whitelaw, 2017).

The tradable fraction of the listed shares now constitutes 75 % of the total number of listed shares. Lastly, China has become the world's largest investors with up to 5 trillion U.S. dollars of total fixed asset investments across the world, passing number two, the United States, (3,7 trillion dollars) and number three, Japan, (1 trillion dollars) combined (Carpenter & Whitelaw, 2017). These remarkable structural changes of China's financial market highlight the growing interdependence between China's financial sector and the financial markets of the rest of the world. Leading to the issue of China's economic integration appearing on the radar of investors and policymakers alike.

2.4 CHINA'S ECONOMIC INTEGRATION

China's integration into the world economy following the collapse of communism constitutes one of the major historical events of the late 20th century and the early 21th century. After initiations of market economic reforms in the 1970s, China stepped up the pace in the 1990s to integrate further into the world economy. The Chinese government embraced a development strategy centered on foreign trade and export-led growth following the example of Japan and South Korea. The Chinese trade efforts gathered considerable speed after China joined the World Trade Organization (WTO) in 2001. In 2000 Chinese exports were in the vicinity of 250 billion U.S. dollars. By 2008 that figure had increased to 1,3 trillion USD (Ferguson & Schularick, 2007).

The economic interdependence between East Asian economies increased significantly during this period. By 1999, intra-regional trade even surpassed that of the European Union. The increase in bilateral-trade was paired with rising levels of capital flows between East Asian countries. Despite the lack of political integration, the economic integration with her closest

neighbors has been one of the key elements in China's rise to becoming an economic powerhouse (Dent, 2017).

The export-led growth strategy also spurred increased interdependence between China and the U.S. economy. The massive Chinese trade surpluses were used in part to purchase U.S. treasuries to keep the Yuan from appreciating and build up U.S. dollar reserves to hedge against financial risks (Ferguson & Schularick, 2007).

This was the start of an intricate economic relationship that had major consequences for not just the two countries involved but the world economy as a whole (Ferguson & Schularick, 2011).

As the U.S. specializes in finance and business administration China specialized in manufacturing products that they exported in large quantities to the U.S. The trade surpluses raised in China was borrowed to the U.S. fuelling even more consumption of Chinese goods and depressing America's interest rates. Essentially the relationship was founded on China doing most of the lending, production and saving while the U.S consumed, borrowed and imported (Ferguson & Schularick, 2007).

Together the two countries account for one-third of the world economy. Total merchandise trade has increased from 2 billion USD in 1979 to 579 billion in 2016. China is the U.S. second biggest merchandise trading partner, third largest export market and largest source of imports (Ferguson & Schularick, 2011). Despite the increased interdependence, there's still uncertainties of the degree of economic integration between the two countries and how that interdependence relates to the stability of the financial markets.

This has led to a growing body of literature that explores how economic shocks in one country would transmit to the other. The interests in the contagious effect of shocks have led to an increase in the number of studies using VAR or VECM models. Many of the studies are focused on the integration of financial markets and test whether returns in China can be explained by variations in macroeconomic variables in the U.S. Few studies have concluded that the two financial markets have reached complete integration, which financial theory defines as assets with the same risk having the same expected returns, regardless of market (Bekaert & Harvey, 1994).

Narayan and Narayan (2012) investigated the effect of changes in the U.S. exchange rate and the short-term interest rate on stock market returns in seven Asian economies, including

China. Using daily data from 2000-2010 they found that the interest-rate had no statistically significant effect on stock market returns in China, however, China was the only country where U.S. currency appreciation didn't have a negative effect on stock returns. The findings suggest that changes in U.S. monetary policy had little effect on Chinese stock returns (Narayan & Narayan, 2012).

Nasser and Hajilee (2016) found that no long-run cointegrated relationship existed between the US and Chinese stock returns but that a relationship existed in the short-term. Huyghebaert and Wang (2009) used a multivariate VAR model, Granger causality, and impulse response analysis to conclude that U.S stock market returns have low predictive ability for Mainland China's stock returns compared to stock returns in Singapore, Hongkong, and Japan during and after the Asian financial crisis in 1997-1998.

Goh et. al. (2012) studied the returns for Chinese A-shares on the Shenzhen and Shanghai stock exchanges as well as industry-specific portfolios ranging from mining to information technology from July 1993 to December 2008. Using principal component analysis, with 14 different U.S. macroeconomic variables, they found that only the inflation variable was significant at a 5 % level and could explain variations in Chinese stock returns on the aggregate market (Goh et. al, 2012).

However, when limiting the dataset to only containing observations from the period after China joined the WTO, five variables were suddenly statistically significant. The findings followed a similar pattern for the thirteen industry portfolios with increasing predictability for U.S macro shocks after China joined the WTO. The results suggest that China's increased financial and economic integration with the world economy following their inclusion into the WTO has led to increased transmissive effects between the two economies (Goh et. al, 2012).

Hurley (2009) focus her study on the relationship between China's large-scale purchases of U.S treasury bills and the U.S. long- and short-term interest rates. Due to the presence of cointegration, the study employs a VECM approach to the Granger causality tests, as well as Impulse Response Analysis, to conclude that the U.S. Dollar-Yuan exchange rate and the Chinese purchase of U.S. treasury bills can exert influence on the U.S. 10-year interest rate. The more treasury bills China purchases the lower is the U.S. 10-year interest rate according to the study (Hurley, 2009).

Even though the literature on the transmissive effects from foreign macroeconomic variables to China's stock markets is a growing field of study, much remains left to be investigated and

many of the studies show conflicting results. The question of the extent of financial integration between China and the rest of the world remains largely unanswered. The growing financial flows, investments and trade between China and the European Union have sparked increased interest in the effects that economic shocks in the EU have on Chinese stock returns. However, unlike the U.S. case, noticeably few studies have been conducted on the topic so far, despite the close interdependence between the EU and China.

China's investments in the EU has increased significantly since the Great Recession that took off in 2008. Since many European companies suffered severe losses during the crisis, many sold shares in their companies at a discount rate to Chinese investors. Back in 2008 Chinese FDI in the EU stood at 1 billion U.S. dollars, by 2014 it had reached 18 billion and it continues to grow (Hung, 2016). China has become EUs biggest supplier of goods while being its second largest export market. The European Union, on the other hand, has become China's biggest trading partner overall (Levinger & Hansakul, 2016).

Yang and Hamori (2013) have carried out one of the relatively few studies into the relationship between US, UK, EU and Japan stock return shocks and the transmissive effect on Brazil, Russia, India, and China. They applied a Copula-GARCH analysis from 25 July 2002 to 13 February 2013. They discovered that developed economies, represented by the EU, US, UK, and Japan had considerable transmissive effects of their stock market shocks, leading to shocks spreading to the stock markets of the BRICs countries. However, the reverse relationship didn't hold (Yang & Hamori, 2013).

Shen, Li, Wang, and Su (2015) used stock market indices for the eurozone to predict returns on the Chinese stock market. To control for global shocks, they included additional macroeconomic variables for the trade balance, exchange rates, and the S&P 500 indices. During the period 2005-2013, the time varying parameter correlation coefficient employed in the study suggested that crisis contagion, where stock market downturns in one country affect the stock market of another, was present between the Eurozone and China. The study also used variance analysis and found that the global macroeconomic shocks also played a significant role in explaining Chinese stock returns, suggesting that China's stock market is influenced by events unfolding on the global stock markets as well (Shen et. al., 2015).

The lack of studies conducted on the relationship between shocks in the EU and subsequent spill-over effects in China highlights the need for additional studies on the topic. Despite the many studies on financial integration overall, there is no widely held notion of exactly how

much financial integration is desirable and to what extent the world financial markets have achieved integration.

2.5 SELECTING MACROECONOMIC VARIABLES

In this paper, four variables will be used to predict which effect macroeconomic shocks in the EU and the U.S. have on Chinese stock indices. This leads to the delicate issue of choosing the correct macroeconomic variables to use. On the one hand, it would be desirable to identify macroeconomic variables that act as a proxy for the general economic state to provide insights on whether shocks to the economy transmits to the stock markets of other economies. This type of proxy variable could produce information on the contagion effects of the booms and busts of one country's business cycle to another. On the other hand, pinpointing specific variables that show an enhanced (or negligible) capability to explain stock market shocks can give detailed information to both policymakers and investors on which economic factors are particularly important to observe.

It is in the light of this background that this paper tries to balance between these two sometimes overlapping and sometimes conflicting objectives. It is also because of this that this paper refrains from using variables such as GDP or aggregate demand that is deemed more general in nature. The four variables, imports, the central bank's short-term interest rate, inflation and industrial production, are therefore necessary to motivate from a theoretical perspective.

The import variable that contains data on EU and U.S. respective imports from China is a suitable variable since it covers much of the economic activity between the countries involved. China has centered its development model around an export-driven growth strategy for decades (Guo & N'Diaye, 2009). Shocks in the imports from the country's two biggest trading partners would be likely to constitute a major macroeconomic shock originating from abroad that could potentially transmit to China's stock market. Within academia concern over the long-term sustainability of China's export-driven growth is increasing, not in the least due to recent events highlighting the prospect of a US-China trade war. Forbes and Chinn (2003) found that trade flows are the most significant factor in explaining contagion effects from the stock market volatility in one economy to the next, making the import variable a suitable pick for this study.

According to Goh et. al. (2012), the inflation variable was the only significant variable out of 14 macroeconomic variables that could explain Chinese stock market returns, independent of

time. This result also follows in line with that of Roll and Ross (1980) who were among the first to try to identify which macroeconomic variables shared a relationship with stock market returns. In recent decades inflation rates in the developed economies have been considerably lower than during previous decades (Arias, Erceg & Trabandt, 2016). Including the inflation, variable is therefore motivated due to its relevance in past studies but also as an opportunity to study whether that relevance is diminishing.

Industrial production was identified as a significant variable in explaining stock returns in Roll and Ross (1980). In Chen, Roll, and Ross (1986) this relationship proved to be even stronger. However, in recent decades the industrial productions share of GDP has declined considerably in the U.S, the EU and the world at large (World Bank, 2016). Shocks in the variable have proved to have an impact on stock returns in the past but including it in more recent data might provide insights to whether that relationship has altered and if the impact of the variable differs between economies.

Monetary policy is believed to influence stock markets through the so-called "monetary transmission mechanism" where asset prices and fundamental macroeconomic conditions are affected by central bank policy. These effects are usually achieved either through the traditional interest rate channel or the credit channel (Mishkin, 1996). This paper uses the Federal Reserve's federal funds rate and the European Central Bank short-term interest rate to assess the spill-over effects of the interest rate channel in the Chinese stock market. Kasi, Wagan, and Akbar (2012) found significant spill-over effects from shocks in the Federal Reserve rate for 14 OECD countries, suggesting that there is such a relationship under integrated financial markets. Including this variable for both the EU and the U.S. creates a chance to explore the effect of monetary policy on the Chinese stock market and determine the nature of financial market convergence between their respective economies.

2.6 INDUSTRY-SPECIFIC EFFECTS

According to financial theory whenever a group of securities is not perfectly correlated an investor can diversify by spreading the investments over multiple assets. Based on this theory much research has been performed on the study of the correlation between different assets or groups of assets, usually divided either by region, industry or size (Cao, Long, Yang, 2013). Studies based on co-movements of national stock prices has received plenty of attention in the literature while sector-based co-movements is a much less investigated area (Meric, Ratner & Meric, 2005).

King (1966) was one of the first to discover that industry factors play a part in explaining differences in stock returns. Livingston (1977) found that 26 % of the volatility of stock returns are a result of industry-specific factors. Cao, Long, Yang (2013) found that in the Shanghai stock market, sector indices tended to rise and fall simultaneously during drastic market shocks. However, this tendency between different sector indices to move together was significantly smaller during periods with a less volatile market.

Three key industry indices will be included in this study to account for industry-specific responses to shocks in the macroeconomic variables of the EU and U.S. respectively. Further studies in this area would be useful to assess whether the response to shocks differs between China's key industries. This is a little-studied area with Go et al. (2012) as one of few exceptions that tracked the impact of shocks in U.S. macroeconomic variables for 13 industry indices on the Shanghai stock exchange but without finding significant industry-specific effects.

The CSI 300 Information Technology Index is included in this model since the information-tech industry is one of the fastest growing industries in China, surpassing even key industries such as steel and oil in terms of sales growth. The industry has been rewarded the title of pillar industry by the government and is the biggest industry in terms of output (Greeven, 2006). The sectors central role in China's economic development makes it an especially interesting topic of study for investors and policymakers.

The CSI 300 Industrials Index includes the return of the company stock of industrial firms ranging from aerospace and machinery to construction and transportation infrastructure. The industrial base was elementary in China's ascent towards becoming one of the world biggest economies and the world's leading exporter (Albala-Bertrand, 2010). The key role of China's manufacturing industry motivates why this index is included in the study. However, the CSI 300 Industrials covers only parts of the manufacturing base in China and excludes vital industries. Therefore, the CSI 300 Materials Index is included to account for China's heavy industries in the chemicals, mining, forest, and paper sectors that also plays a vital role in the Chinese economy (Albala-Bertrand, 2010).

3. METHODOLOGY AND RESULTS

This paper analyzes the relationship between investments on the Chinese stock market and macroeconomic variables from the U.S. and EU respectively, for the period covering January 2008 to December 2017, using monthly data. Vector autoregression (VAR) tools such as

causality, impulse response functions, and variance decomposition are employed to examine the inter-relationships among the variables.

Four different indices – Shanghai Composite Index, CSI 300 Information Technology, CSI 300 Material and CSI 300 Industrials - are used to observe the investments in the Chinese stock market. The former is a broad index containing 500 companies from various sectors and is used as a proxy for the overall investments on the Chinese market. The latter three contain 300 companies each and reflect the investments in a specific sector. Information Technology contains companies operating in software & services, technology hardware & equipment, and semiconductors & semiconductor Equipment etc. Materials contains companies within chemical production, metals & mining, paper & forest products and construction materials etc. Lastly, Industrial Production contains companies operating within areas of aerospace & defense, building products, construction engineering, transportation infrastructure and machinery etc.

The macroeconomic variables for the U.S. – imports, the federal funds rate, industrial production and the inflation rate – are obtained from Federal Reserve Bank of St. Louis. All the macroeconomic variables for EU – import, the short-term European central bank rate, industrial production and the inflation rate – are obtained from the OECD database, except for the European central bank rate which was collected from the European Central Bank's Statistical Data Warehouse.

3.1 MODEL SPECIFICATION AND SELECTION

The inter-relationship between the indices and the macroeconomic variables have been evaluated in four different models for both the U.S. and EU, resulting in eight different models in total. The models have been ordered as follows:

Models for the U.S.:

- SHANG(US): *SHCOMP, IMPORT (US), FED RATE, INDUSTRIAL PRODUCTION (US), INFLATION (US)*
- INFO(US): *CSI INFORMATION TECH, IMPORT (US), FED RATE, INDUSTRIAL PRODUCTION (US), INFLATION (US)*
- MATERIAL(US): *CSI MATERIAL, IMPORT (US), FED RATE, INDUSTRIAL PRODUCTION (US), INFLATION (US)*
- INDP(US): *CSI INDUSTRIAL, IMPORT (US), FED RATE, INDUSTRIAL PRODUCTION (US), INFLATION (US)*

Models for the EU:

- SHANG(EU): *SHCOMP, IMPORT (EU), ECB RATE, INDUSTRIAL PRODUCTION (EU), INFLATION (EU)*
- INFO(EU): *CSI INFORMATION TECH, IMPORT (EU), ECB RATE, INDUSTRIAL PRODUCTION (EU), INFLATION (EU)*
- MATERIAL(EU): *CSI MATERIAL, IMPORT (EU), ECB RATE, INDUSTRIAL PRODUCTION (EU), INFLATION (EU)*
- INDP(EU): *CSI INDUSTRIAL, IMPORT (EU), ECB RATE, INDUSTRIAL PRODUCTION (EU), INFLATION (EU)*

Where SHCOMP is Shanghai Composite Index, CSI INFORMATION TECH is the CSI 300 Information Technology Index, CSI MATERIAL is the CSI 300 Materials Index and CSI INDUSTRIAL is the CSI 300 Industrial Production Index.

Before evaluating the relationships between the variables, the Augmented Dickey-Fuller and Phillips-Perron tests are performed to establish the potential presence of unit roots (tables 33 - 56, see Appendix). All-time series are found to be stationary in first differences at a 95 % confidence level. Even though the time series are nonstationary in levels, there may exist a linear combination that is stationary between them. If such a long-run stochastic trend is present the variables will have a close relationship and common characteristics will bring them back together in case of deviations from their set path, due to shocks. If cointegration exists then causality is running between the time series in at least one direction (Engle & Granger, 1987).

Prior to testing for cointegration, the optimal lag length is determined by running the VAR models in levels, which, based on the Schwarz information criterion and Akaike information criterion, was determined at 2 lags for all models. Following the optimal lag length selection, the Johansen cointegration test is used to investigate the long-run relationship. The Johansen method, which is based on the maximum likelihood estimation of the VAR model, uses two likelihood ratio tests (maximum eigenvalue and trace tests) to establish the number of cointegration vectors (Johansen, 1991).

The results are reported in tables 17 – 24 (see Appendix), and according to the trace test results, all models have at least one cointegration vector at 95 % confidence level, except for SHANG(US) and INDP(US) which have one cointegration vector at a 90 % confidence level.

The maximum eigenvalue test results suggest the presence of one cointegration vector at a 95 % confidence level for all models except for SHANG(EU), MATERIALS(US) and INDP(US) which have one cointegration vector at 90 % confidence level. The combined test results point towards the existence of a long-run equilibrium relationship among the time series.

With cointegration established, causality tests based on the vector error correction method (VEC) are performed. The method includes an error correction mechanism (ECM) term which considers the residuals from the cointegration regression. The ECM term in the model refers to the fact that the last period's deviation from a long-run equilibrium influences its short-run dynamics (Engle & Granger, 1987). The VEC Granger causality test is also performed to test for the presence of significant estimators in the off-diagonal VAR presentation.

Following the causality testing, the impulse response functions and variance decomposition are employed to examine the dynamics of the variable relationships. The impulse response function analysis establishes the direction as well as the time path of the response of the endogenous variable to a shock on itself and the other endogenous variables (Enders, 2015).

While the impulse responses are assigned to explain the direction, the variance decomposition is employed to establish the relative importance of a shock in each of the time series in explaining other data series within the models. The variance decomposition determines how much of the future uncertainty of dependent series is due to future shocks in the other time series in the system. Both the variance decomposition and the impulse response function have been ordered using the Cholesky distribution which, by restricting the causality in one direction, allows for experiments in which any variable is independently shocked (Enders, 2015). The two methods are often sensitive to the ordering selected; the ordering used is guided by the causality findings presented below.

3.2 SUMMARY OF RESULTS

Tables 9 to 16 report the findings from the VEC model and tables 25 to 32 report the findings from the VEC Granger test (see Appendix). The ECM term is statistically significant for all stock indices for both the U.S. and EU, as well as showing oscillating convergence which indicates that they will adjust back towards the long-run equilibrium following a shock. However, this cannot be seen in the impulse response functions, but rather it appears that the responses following a shock are somewhat persistent. Something that could be due to the low

speed-of-adjustment terms for all the indices. The presence of both long-run and short-run causality in the stock indices is found only in SHANG(EU) and MATERIAL(EU).

The speed-of-adjustment towards the long-run equilibrium (absolute value of the ECM term) indicates that the stock indices will adjust in a faster pace - following a shock in the U.S compared to the EU - for all indices except the CSI 300 Industrial Production Index which will adjust with 4 % per month for both. The biggest difference in the speed-of-adjustment is found in the two SHANG models, which adjust at 7 % per month for SHANG(US) and 2 % per month for SHANG(EU).

The causality findings indicate no unidirectional causality running from any of the macroeconomic variables to the stock indices except for the MATERIAL(EU) where the European central bank rate is Granger causing the CSI 300 Materials Index.

Graphs 1 to 8 (see Appendix) show the response of the indices to a one standard deviation shock in each of the five endogenous variables for horizons 1 through 36 months, using the Cholesky ordering discussed in the previous chapter. The ordering used in all models is guided by the causality findings for each model and is as follows:

- SHANG(US): *SHCOMP, industrial production, federal funds rate, import, and inflation.*
- SHANG(EU): *SHCOMP, industrial production, European central bank rate, inflation, and import.*
- INFO(US): *CSI 300 Information Technology Index, industrial production, federal funds rate, import, and inflation.*
- INFO(EU): *CSI 300 Information Technology Index, industrial production, inflation, European central bank rate and import.*
- MATERIAL(US): *CSI 300 Material Index, industrial production, federal funds rate, import and inflation.*
- MATERIAL(EU): *European central bank rate, CSI 300 Materials Index, import, industrial production and inflation.*
- INDP(US): *CSI 300 Industrial Production, industrial production, federal funds rate, import, and inflation.*
- INDP(EU): *CSI 300 Industrial Production, European central bank rate, industrial production, inflation and import.*

The impulse response findings show a positive response in all the indices in response to a positive one standard deviation shock in imports in the U.S., but a negative response to an equivalent shock in any of the other American macroeconomic variables. For shocks in the EU-variables, the responses are a bit more diverse. Both the CSI 300 Information Technology Index and the CSI 300 Industrial Production Index have positive responses regarding shocks in import, the European central bank rate, and industrial production, but, respond negatively to a shock in inflation. The SHCOMP and the CSI 300 Materials Index, on the other hand, have a positive response to a shock in import and industrial production, but, a negative response to a shock in the European central bank rate and inflation.

The responses - of the indices in all US models to shocks in the macroeconomic variables – lie between positive 10 % to negative 20 %, with import causing the most positive response (~ 10 %) and inflation causing the most negative response (~ -18 %) at the 36 months point. The responses, of the indices in all EU models to shocks in the macroeconomic variables, lie between positive 10 % to negative 10 %, with import causing the most positive response (~ 10 %) and inflation causing the most negative response (~ -10 %) at the 36 months point.

For the U.S variables, all indices (except for CSI 300 Industrial Production) responds, after the first six months, more negatively to a shock in the industrial production than to a shock in the federal funds rate. The CSI 300 Industrial Production responds more negatively to a shock in the federal funds rate than to a shock in industrial production during the first year. Around the twelve months mark the responses to the two macroeconomic variables converges and become almost identical. For the EU macroeconomic variables, all the indices (except for CSI 300 Industrial Production) respond, after the first six months, more negatively to a shock in the industrial production than a shock in the ECB rate. The CSI 300 Industrial Production Index responds more negatively to a shock in the federal funds rate than to a shock in the industrial production during the first year. Around the twelve months mark the responses to the two macroeconomic variables converge and become almost identical.

A similar but mirrored trend is found in the responses of the indices to shocks in the EU variables. The response of all the indices (except for CSI 300 Industrial Production) is more positive to a shock in the industrial production than to a shock in the European central bank rate. The CSI 300 Industrial Production Index responses to shocks in the industrial production and the European central bank rate converge around the 20 months mark. The CSI 300 Industrial Production Index has a positive response to a shock in the industrial production during the entire time horizon, while it has a positive response to a shock in the European

central bank rate during the first four months, a negative response from months five to ten and a more positive response than industrial production from month twelve to the convergence occurs at months 20.

Tables 1 to 8 report the findings of the variance decomposition for the five endogenous variables for forecast horizons up to 36 months (see Appendix). For the U.S. models, the indices themselves stand for the biggest forecast variation, all having a share over 55 % at the 36 months mark. The variance decomposition also indicates that inflation is explaining the second largest share of the variation in all indices apart from in the CSI 300 Materials, where the import explains a larger share. The federal funds rate has the lowest share in explaining the relative variation in all the indices, not passing over 2 % for any stock index. Also, the share of the federal funds rate increases through month one to six, but then it starts to decrease after month six to the end of the forecast horizon, except for the INDP(US) model where it starts to decline at month twelve.

Looking at the share of each of the variables in explaining the relative variation of the four stock indices regarding the EU macroeconomic variables, the indices themselves stand for the biggest forecast variation, all having a share over 75 % at the 36 months mark. The variance decomposition also indicates that import is explaining the second largest share of the variation in all indices apart from in the SHCOMP where inflation explains a larger share. The European central bank rate has the lowest share in explaining the relative variation in all the indices, not passing over 3 % for any stock index.

The indices in the EU models explain their own variation to a larger extent than for the indices in U.S. models, apart from the INPD models. The findings also suggest that import is more important for the U.S models than for the EU models, except for the INPD models. Also, inflation is explaining a large share of the relative variation in the U.S. models compared to the EU models.

3.3 LIMITATIONS

The data used in this paper covers the period of the Great Recession (2008-2012) and therefore it is plausible that the unnaturally large movements captured in the data during this period exercise influence over the results from the VAR analysis. The direction of the responses in the impulse response analysis is probably the most sensitive to abnormal movements in the data. While the 2008 financial crisis is heavily reflected in all the macroeconomic variables for both the U.S. and EU, the 2011 Euro crisis is not nearly as

pronounced in any of the time series. Furthermore, all macroeconomic time series show similar patterns except for the interest rates which is slightly increasing for the U.S. and slightly decreasing for EU during the whole period. This would naturally influence the direction of a response following a shock. However, the variance decomposition clearly shows that the interest rates exert a limited influence in explaining the stock indices for all models, thus, reducing the impact of abnormal data movements within the interest rate time series.

Further limitations lies in the frequency of the data. Most macroeconomic data are collected annually, quarterly or, in more rare cases, monthly. Daily or weekly data is more difficult to obtain and that should be factored into the analysis of the results. This study might have produced different results if daily or weekly macroeconomic data was used, rather than monthly, which readers should be aware of.

The Chinese government is known to intervene in the stock market in case of severe volatility. Most countries intervene in the financial system to some degree through regulation, bank bailouts or similar means, however, given the tendency of China to go further than most other nations in this area, it is possible that the results from this study has been skewed to some degree by Chinese government interventions during the study's time-frame. Such effects are hard to detect and test for, but readers should at least be aware that such interventions might have altered the results compared to a counter-factual scenario where China's financial markets weren't subject to such far-reaching government interventions.

4. ANALYSIS

4.1 INFLATION

The impulse responses for the inflation variable is consistently negative for the U.S. models, regardless of industry. All Chinese stock indices respond negatively to a positive one standard deviation shock in inflation. The same consistently negative pattern also occurs for all the EU models. The indices initial response is almost equal for the two regions. After 5 months, a positive one standard deviation shock causes a negative response amounting to approximately 10 % for all indices and both regions. However, with time, the negative response to a shock in the U.S. inflation variable increases.

After 15 months the shock response hovers close to negative 20 % for all U.S. models except the CSI 300 Information Technology where the negative response is less pronounced. For the EU models, the shock response stabilizes around negative 10 % after approximately 6 months and do not divert substantially from this pattern after this point. This indicates that there's no distinguishable long-term effect of the shock for the EU models. Rather, the shock response stabilizes after the initial negative response and remains constant for the remainder of the period. For the U.S. models, the shock response tends to increase both in the short-term and long-term up until approximately 15 months.

Regarding the steepness of the curves, there are only small differences between the two regions. The main difference lies in the time aspect, where the initial response is similar, but the negative response to U.S. inflation increases and surpasses that of the EU. The fact that the Chinese indices react more strongly to U.S. shocks in inflation is further highlighted by the results from the variance decomposition. The share of the inflation variable ranges between 5 and 8 % for the EU models after 36 months.

For the U.S. models, the share ranges from 11-18 %. The share of inflation for each EU model is close to half that of the respective US model. As discussed in the literature review, section 2.1, Fama (1981) put forward the claim that inflation is negatively correlated with stock returns. This claim was supported further by Fama (1983), Geska and Roll (1983), Gultekin (1983), Solnik (1983), Kaul (1987) and partly Lifang (2009). Even though studies suggesting a negative correlation between inflation and stock returns outnumber the studies suggesting the opposite relationship, some researchers have concluded that inflation correlates positively with stock returns. Boudoukh and Richardson (1993), Madsen (2005) and Ryan (2006) constitute some of the more influential ones (Lin, 2009).

The method used in this paper tracks the reaction to a positive one deviation shock in inflation. The results indicate that an increase in inflation in both the EU and the U.S. has a negative impact on Chinese stock indices. This result has a strong foundation in the finance literature as mentioned above. Additionally, the result also suggests that the Chinese indices respond stronger to the U.S. than EU inflation shocks. This indicates that the Chinese stock market is more sensitive to shocks in U.S. inflation than EU inflation which could be due to closer financial integration. As mentioned in the literature review, section 2.1, Nasseh and Strauss (2000) stressed that transmission of shocks between macroeconomic conditions of one country and the stock market of another country was a sign of significant financial integration.

Hence, that the U.S. inflation shocks produce a stronger response than the EU inflation shocks indicates a stronger financial integration between China and the U.S. than between China and the EU. The fact that U.S. inflation is a potential factor in explaining Chinese stock return variations is not surprising given the results of Goh et. al. (2012) that found U.S. inflation to have the strongest explanatory power among 14 U.S. macroeconomic variables used to predict Chinese stock returns.

However, the results from the variance decomposition still suggest that the most fundamental factor in explaining the variance of the index is the values of the index itself. In other words, even though the share of the inflation variable in the U.S. models is significantly larger than for the EU models, the inflation variables for both models still have a low capacity to explain the variance compared to the indices themselves. This result is in line with Chen and Yuan (2010) who used Chinese inflation data and found that domestic inflation had a limited ability to explain variations in Chinese Stock returns. According to the model in this paper, the limited explanatory power of inflation seems to hold also for the U.S. and the EU.

Among the macroeconomic variables, inflation is the factor that can explain the highest share of variance for 4 out of 8 models. Yet, this paper lends support to the notion that inflation shocks are not as a substantial of a factor as the indices themselves in explaining the variance of Chinese indices. This holds even though the variance share of U.S. inflation shocks surpasses that of the EU for all models and that Chinese indices generally respond negatively to positive shocks in both EU and U.S. inflation.

4.2 IMPORT

The impulse response functions indicate that a one standard deviation shock in import causes a positive response in all indexes which stays around positive 10 % for all models during the 36 months. While the responses are almost identical between the U.S. and the European Union after the five months mark, all the indices except for CSI 300 Materials reaches the highest point (10 %) much faster for the U.S. than for EU. The steeper response present, following a shock in the American import, indicates a stronger sensitivity towards the U.S. for the Chinese stock market in comparison to EU.

Which also suggests that China is more integrated with the U.S. market (Nasseh & Strauss, 2000). This claim is strengthened by Hurley (2009) which investigated the economic linkages between China and the U.S. and found a strong interdependence between the two economies and their macroeconomic climate. Also, the variance decomposition shows that the U.S.

import explains a larger share of the variance in the indices compared to the EU import (except for the CSI 300 Industrial Production Index). Something that further confirms the findings of a stronger interdependence.

Also, Paramati, Gupta, and Hui (2016) – who examine if the intensity of trade and investments linkages between countries affects their stock markets – found support for the claim that intensity of bilateral trade affects the rate of investment on a country's stock market. And while China has a larger overall exchange of goods with the European Union the U.S. is still the single largest receiver of Chinese exports which also explains why the U.S. imports should contribute with a larger share in the explanation of the variance in the indices. Given the importance of China's export industry for the country's economy this should not be all too surprising.

China's strict monetary policy and its undervalued exchange rate are an important aspect in trying to determine the response of investors to a positive shock in imports. As mentioned earlier in section 2.4, China has kept the Yuan continuously undervalued (mainly against the U.S. dollar) to foster economic growth through export promotion and to mobilize its labor force towards the most productive sectors of its economy (Bonatti & Fracasso, 2013). Along similar lines, Dornbusch and Fischer (1980) argue that fluctuations in a country's exchange rate affect the competitiveness of firms through the values of earnings. They conclude that stock prices tend to increase as a result of the depreciation of local currency since it makes a country's export goods attractive and as foreign demand increase the firms' revenues do as well.

Looking at the variance decomposition the import also contributes in explaining the largest share relative to the other macroeconomic variables in almost all models, after the indices themselves. Also, with the exception of INDP(EU), the import explains a larger share in all US models compared to their EU counterparts. On the basis of the evidence currently available, it seems reasonable to suggest that investors are more sensitive to shocks in the US import.

4.3 INDUSTRIAL PRODUCTION

By taking a closer look at the impulse responses to innovations in the industrial production two striking features stands out. Firstly, all the indices respond negatively to a positive shock in the industrial production for the U.S. and positively following a positive shock in the industrial production in EU. Secondly, for both the U.S. and EU the response in the indices is

increasing at first, but around month three it declines (going below zero in response to the U.S. and stays above zero for EU).

An increased share of industrial production in a region's local market would by definition increase the number of available goods. How this, as a result, affects the stock prices in another country will be linked to the level of trade between them. If the increased share of locally produced goods is put into the local market the foreign country's export companies would face a higher degree of competition. Through supply and demand, it would effectively reduce the import demand which negatively affects the foreign exporting companies (Economidou & Murshid, 2008).

Viewed from the perspective of this paper this means that a positive shock in industrial production in the U.S. would have a negative effect on the Chinese export sector. As already established, China and the U.S. seem to be more dependent on each other compared to China and the EU. Furthermore, since the U.S. is the biggest importer of Chinese goods a shock in industrial production that causes a negative response in the indices must indicate that a large enough share of the goods produced is flooding the local U.S. market. Economidou and Murshid (2008) also found the support that increased import volumes exert a positive influence on the local industries' productivity. Therefore, one cannot exclude the possibility that a positive shock in import causes a positive shock in the industrial production.

However, the foregoing discussion implies that the U.S. produced goods directly compete with the Chinese imports. According to Jarreau and Poncett (2012) China has reached a level of export sophistication comparable to the western countries, but, China's export sophistication is still closely linked to the assembly trade sector and its biggest contribution is the vast labor force while most of the knowledge comes outside of its borders. Along similar lines, Schott (2008) argues that Chinese exports are sold to a significant discount relative to the exports of the OECD countries and because of this the Chinese exports do not compete directly with the goods produced by the western countries. This argument is also strengthened by China's exchange rate policy discussed earlier since an undervalued Yuan relative to the U.S. dollar makes it much cheaper for American consumers to buy the Chinese goods compared to their domestic counterpart (especially consumer electronics).

The above arguments contradict the conclusions drawn from the theory presented by Economidou & Murshid (2008) if the Chinese companies that export to the U.S. do not compete with the U.S. domestic market a shock in industrial production should not have a

distinct effect on the Chinese stock market. The results from the variance decomposition also indicate that, except for in MATERIAL(US), the industrial production explains a quite small share of the variance in the indices relative to the other variables and the indices themselves. Also, the causality findings indicate that no causality is running from the industrial production to the indices in any of the models which emphasize the need to exercise caution when trying to determine which dynamics in the industrial production causes the responses observed in the indices.

There is insufficient research on how the industrial production in one country impacts the stock market in another country to draw any firm conclusions. From the discussion above one can conclude that industrial production has an impact, if yet limited, on the Chinese indices. Even though there is a slightly negative effect, the direction of the shock is perhaps not the most interesting finding in the U.S. case. Analyzed from the viewpoint of the share of industrial production in the variance decomposition, the limited size of the variables makes it difficult to claim that U.S. gains in industrial production transmit to the Chinese stock markets to any meaningful degree. This is also in line with the arguments presented by Schott (2008) and Jarreau & Poncett (2012) that Chinese and U.S. goods do not compete directly with each other.

The above discussions also apply to the European Union but with one important difference. As established before the interdependence is more extensive between China and the U.S. compared to China and EU but the trade between the latter two is more balanced if measured in overall trade. A shock in the industrial production of the European Union should, therefore, have a less pronounced impact compared to the U.S. industrial production in explaining the relative variance of the indices. Something that also is confirmed by observing the results from the variance decomposition for the models. The industrial production for EU has a significantly lower impact in explaining the index variance compared to the U.S. (see Appendix).

The industrial production variable causes a positive response in the Chinese stock indices. The direction of the shock could be explained by the reciprocal trade between China and the EU. As China imports significantly more goods from the EU than the U.S., an increase in EU industrial production would decrease the price of Chinese imports from the EU. As import costs decrease this could transmit to the Chinese stock indices with subsequent gains for Chinese companies that could explain the direction of the shock (Jarreau & Poncett, 2012).

4.4 SHORT-TERM INTEREST RATES

The linkages between monetary policy and asset prices is a well-researched area of economics. Unfortunately, the results are mixed with different studies reaching different conclusions. Early research by Sprinkel (1964), Homa & Jaffe (1971) and Hamburger & Kochin (1972) found ample support that data over money supply could explain variations in stock prices (Laopodis, 2012). Later research conducted by Cooper (1974), Rozeff (1974) and Rogalski & Vinso (1977), among others, found little to no support that stock prices were influenced by the central banks adjustments of short-term interest rates. This was supported by later research from Tarhan (1995), Ceccheti (2003) and Hayford & Malliaris (2004).

Thorbecke (1997) and Rigobon & Sack (2002, 2003, 2004) found evidence contradicting these findings and claimed that increases in the U.S. federal funds rate had significant negative impacts on U.S. stock indices (Laopodis, 2012). In Rigobon and Sack (2002), a 25-basis point interest rate hike resulted in a corresponding decrease of the S&P 500 Index by 1, 9% and a 2,5 % decrease in the Nasdaq index.

In general, most studies that have identified a relationship between central bank interest rates and asset prices have concluded that the relationship is negatively correlated. This is explained by the depressing effects that increasing central bank rates have on the money supply and the cost of financing. Other studies have claimed that the relationship is the reverse, where higher rates lead to lower inflation which in turn leads to higher stock prices (Bjørnland & Leitemo, 2008).

Most previous research has focused on the impact of the U.S. federal funds rate on domestic stock markets. Bohl, Siklos & Sondermann (2008) estimated the reaction by European stock markets to rate adjustments of the ECB. They found a significant negative impact on stock performances as the ECB hiked up interest rates. With a 25-basis points interest rate-hike, European stock markets decreased between 1, 42 % and 2, 3 % (Bohl, Siklos & Sondermann, 2008).

Kholodilin, Montagnoli, Napolitano & Siliverstovs (2009) tracked the impact of ECB interest rate adjustments across different sectors. A 25-basis point hike resulted in stock market decreases by approximately 0, 3-2% with the telecommunications sector being impacted the most (Bao & Mateus, 2017).

With a global rise in financial integration, several studies have tried to estimate the transmissive effect of interest rate adjustments from one central bank to another country's

stock market. Most studies of this kind focus on the impact of the federal funds rate on foreign markets.

The effect could either spread indirectly through central banks, where the federal reserve adjustments lead to similar responses by other central banks that impact the stock performances, or more directly, by adjustments in the U.S. affecting the mood of investors in a positive or negative direction depending on the nature of the interest rate adjustment. Due to high financial integration and close trade ties, U.S. monetary policy is highly correlated to monetary policy, and the subsequent spill-over effects on the stock markets, in France, Germany, Italy and many other developed European countries (Bao & Matues, 2017). Japan, on the other hand, stands out as a developed country with strong trade and financial ties with the U.S. but with low monetary policy convergence.

Bao and Matues (2017) also found a strong correlation between U.S. federal funds rate adjustments and the monetary policy of Thailand, Indonesia, Malaysia, Singapore and The Philippines. Valente (2008) found a strong correlation for both Singapore and Hong Kong. Surprisingly little research has been conducted on the monetary policy linkages between China, the U.S. and EU, despite ever-closer trade and financial linkages.

The results of this paper show a negative index response to a one standard deviation shock in the federal funds rate for all four U.S. models. The negative effect is smaller than for the inflation variable but there are clear signs of mean reversion. The negative response fits well with both financial theory and previous research such as Rigobon and Sack (2002, 2003, 2004). However, the actual effect is small which is evident from both the impulse response function and the variance decomposition.

The share of the variance never surpasses 2 % of the shock, which weakens the notion that the federal funds rate is a key variable in explaining movements in the Chinese indices. This is conspicuous, regardless of industry. The reason for this result is difficult to assess but it could be an indication that China either is insufficiently financially integrated with the U.S., leading to a low convergence between the U.S. monetary policy and Chinese stock indices (Nasseh & Strauss, 2000).

Or that investors tend to downplay the federal fund's rates spill-over effects on the Chinese economy. Federal funds rate-hikes are usually employed to cool down a booming economy and prevent inflation, but if investors believe that the effect of a U.S. cooldown wouldn’t transmit to China, then they might not see a reason to sell of their holdings (Laopodis, 2012).

The result for the EU models is perhaps even more puzzling. For the Information tech Index and the Industrials index, there is a small, positive response to a one standard deviation shock in the ECB interest rate. For the Shanghai Composite index and the Materials index, there is a small, negative response with a tendency to revert to the mean. The share of the ECB rate in the variance decomposition is between 0-3,7 %, which is slightly higher than the U.S. models but still low to a degree where it's difficult to state that the ECB rate is a key variable in explaining shocks to Chinese indices.

The fact that the response is positive for some indices could be an indication that the theory proposed by some scholars, that interest rate-hikes lowers inflation and thereby pushes stock returns upwards, could be plausible but given the small effect and the conflicting results in other indices, it's not credible to draw such far-reaching conclusions.

4.5 INDEX SPECIFIC

A striking feature from the VECM outputs is that the speed-of-adjustment terms indicate that the indices adjust back to equilibrium faster following a shock in the U.S. macroeconomic variables compared to a similar shock in the EU variables. According to Nasseh & Strauss (2000), this would further strengthen the arguments of the financial cointegration between China and the U.S., being stronger compared to the relationship between China and EU. This is also consistent with the findings from the variance decompositions which indicates the macroeconomic variables, in explaining the relative variance of the indices, is higher in all the U.S. models compared to their EU counterparts. In the EU models, the indices explain most of their own variance. These findings indicate that the Chinese companies are not as sensitive to potential shocks in the macroeconomic climate in EU, as they are too similar shocks in the U.S.

Another noticeable finding is the differences between the CSI Materials and the CSI Industrials indices. China is the world single largest producer of gold, coal and many of the world's rare earth minerals. China's largest commodity companies are included in the CSI Materials index. Several studies have claimed that commodity prices are determined on the world markets rather than the domestic, primarily through the trade in commodity futures on the world's stock markets (U.S. Department of Commerce, 2017).

Volatility on the world's commodity markets is therefore likely to transmit to the domestic commodity industries. Due to the material industries integration with the global markets, it is possible that shocks in other countries would transmit more explicitly compared to industries

with a lower degree of integration. It is therefore interesting to note that the macroeconomic variables for the U.S. CSI Materials model can explain the largest share of the variance. 41,04 % of the variance can be accounted for by the U.S. macroeconomic variables. The U.S. import variable can also explain more of the variance for this index compared to the three other U.S. indices, 13, 56 %.

The fact that this index consists of companies dependent on world commodity prices and exports to other countries could be a factor in explaining these results. The more international companies are the more sensitive should they be to shocks occurring in foreign or world markets. A shock in U.S. macroeconomic variables tends to affect the materials industry to a larger extent than other indices.

This finding is supported by the equivalent result for the CSI Industrials index. The CSI Industrials index consists of companies in the defense-, infrastructure, transport, and aerospace industry. The companies are skewed towards production for the domestic market and many receive their largest revenues from state and local government contracts (CSI Index, 2018). In other words, they are largely protected from sudden shifts in the world's stock markets due to the nature of their revenues and the stability of many government contracts. A mere 22, 57 % of the variance can be explained by U.S. macroeconomic shocks, the lowest share of all U.S. model.

The variance decomposition share of the U.S. import variable is also significantly smaller (8, 46%) for this model compared to the model for the CSI Materials index. For the EU models, neither the variance for the CSI Industrials index (22,82 %) or for the CSI Materials index (22, 51%) can be explained to a large extent by EU macroeconomic variables.

Combined, these results could be an indication that export-oriented and commodity industries are more sensitive to U.S. macroeconomic shocks than industries that have closer economic linkages to the domestic market. The fact that this relationship is only visible for the U.S. models but not for the EU is likely a reflection of the EU having a lower degree of integration with China, as suggested previously.

5. CONCLUSION

In recent decades, China's integration into the world economy has created new economic linkages between China and the U.S. and between China and the European Union. In the areas

of bilateral trade and finance, the relationships have grown ever closer as China pursues its successful export-driven growth policy. While the trade relationships between China and the U.S. is more unidirectional, with U.S. importing far more from China than it exports, EU and China's trade relationship have moved towards reciprocity with both large export and import flows. This raises the question whether the European Union has caught up to the U.S. in terms of their interdependence with China and the level of China's exposure to macroeconomic shocks. Most previous research on macroeconomic effects on the Chinese stock market has been oriented towards domestic macro shocks. Some have incorporated U.S. macroeconomic variables, but the numbers of studies remain few and even fewer have researched the transmission of EUs macroeconomic shocks to China.

This paper compares China's response to macroeconomic shocks from both the EU and U.S. economies. The purpose is to provide insights for investors looking to invest in the Chinese stock market and for policymaking within a Chinese context. The results of the VECM, impulse response functions and variance decompositions suggest that out of the four variables, import and inflation are the most significant variables in terms of their transmissive effects on the Chinese stock markets, following a shock. The effect of the central bank rates and industrial production are significantly smaller and cannot reasonably be claimed to explain Chinese stock variations, at least in the context of this model and data set.

This pattern is present both in the U.S. and the EU case, but the share of the import and inflation variables are noticeably larger for the U.S. models which indicates stronger transmissive effects from U.S. macroeconomic shocks than from the European Union. The stronger transmission effects are an indication of stronger financial integration between China and the U.S. since close financial integration would cause convergent economic conditions where a shock in one market would produce contagious effects in other financially integrated markets. The result suggests that a positive shock in U.S. inflation and imports risks leading to spill-over effects in the Chinese stock market, both for the broader market and the specific industries. For inflation the response is negative and for imports, it is positive which can be of considerable value for policymakers and investors.

If policymakers are unable to contain rising U.S. inflation this might produce lower stock returns in the Chinese market while an increase in U.S. imports is likely to produce the opposite outcome. For the EU, the direction would likely be similar but with a less pronounced effect due to lower financial integration with China.

That neither shocks to the federal funds rate or the ECB rate showed a sign of transmitting effects to the Chinese indices suggests a resilience of Chinese stock returns to rising central bank rates in the U.S. and the EU. The variable had little explanatory value for the Chinese stock market. Industrial production can also not be considered to affect the Chinese stock returns in any noticeable degree. Nevertheless, the results which shows a positive response in the indices following a shock in EU could be an indicator that a bidirectional trade pattern could be more beneficial compared to the current unidirectional trade between China and the U.S. and that China would be better off by balancing the trade to a higher degree in order to reduce its current dependence to the U.S. However, if Chinese policymakers should, in fact, try to pursue such policies is outside the scope of this paper and will be left to future research to decide.

Future research would do well to delve deeper into whether Chinese exports compete with the domestically produced U.S. goods to a larger extent than what previous research has concluded. The direction of the indices' responses, following a shock in industrial production, was one of the most puzzling results in this paper. Another interesting area for future research would be to study the spill-over effects of negative shocks. The analysis in this paper is limited to the response of a positive one standard deviation shock but gives no indication of the response to a negative shock in the macroeconomic variables. It is possible that a negative shock would be symmetric so that it would be a mirror-image of the positive shock's, but as much financial literature has concluded, markets tend to react stronger to negative volatility than positive, which could suggest that the response to a negative shock would differ from the findings in this study.

The study of the transmissive effects of monetary policy is limited to the interest-rate channel. Future research could provide additional insights by studying the impact of other forms of monetary policy instruments in the Chinese market, such as the credit channel. Given China's closer integration with the world's financial markets in recent decades, it would also be interesting if future studies repeated this study in the future since the result is likely to hinge on the degree of financial integration. If recent long-term trends persist with China becoming even more financially integrated with world markets as time progresses it would be plausible that the transmissive effects from the U.S. or EU markets increased, generating closer market convergence between them.

REFERENCES

Agènor, P. (2003). "Benefits and Costs of International Financial Integration: Theory and Facts", *The World Economy,* vol. 26, pp. 1089- 1118

Albala-Bertrand, J.M. (2010). "Structural Change in Industrial Output: China 1995-2010", *Journal of Chinese Economic and Foreign Trade Studies,* vol. 9(2) pp. 146-170

Arias, J., Erceg, C., & Trabandt, M. (2016). "The Macroeconomic Risks of Undesirably Low Inflation", *European Economic Review,* vol. 88, pp 88-107

Bao, T., & Mateus, C. (2017). "Impact of FOMC Announcement on Stock Price Index in Southeast Asian Countries", *China Finance Review International,* vol. 7, pp. 1-24

Becker, K., Finnerty, J., & Kopecky, K. (1995). "Domestic Macroeconomic News and Foreign Interest Rates", *Journal of International Money and Finance,* vol. 14, pp. 763-783

Bekaert, G., & Harvey, C. (1994). "Time-varying World Market Integration", *National Bureau of Economic Research,* no. 4843, pp 1-35

Bjørnland, H., & Leitemo, K. (2008). "Identifying the Interdependence between U.S. Monetary Policy and the Stock Market", vol. 56(2), pp. 275-282

Brunnermeier, M., Sockin, M., & Xiong, W. (2017). "China's Gradualistic Economic Approach and Financial Markets", *American Economic Review,* vol. 107, pp. 608-613

Bohl, M., Siklos, P., & Sondermann, D. (2008). "European Stock Markets and the ECB's Monetary Policy Surprises", *International Finance,* vol. 11(2), pp. 117-130

Bonatti, L., & Fracassi, A., (2013). "Hoarding of International Reserves in China: Mercantilism, Domestic Consumption and U.S. Monetary Policy", *Journal of International Money and Finance*, vol. 32(3), pp. 1044 - 1078, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 13 May 2018]

Boyd, J., & Smith, B. (1992). "Intermediation and the Equilibrium Allocation of Investment Capital: Implications for Economic Development", *Journal of Monetary Economics,* vol. 30, pp. 409-432

Cao, D., Long, W., & Yang, W. (2013). "Sector Indices Correlation Analysis in China's Stock Market", *Procedia Computer Science,* vol. 17, pp. 1241-1249

Carpenter, J., & Whitelaw, R. (2017). "The Development of China's Stock Market and Stakes for the Global Economy", *Annual Review of Financial Economics,* vol. 9, pp. 233-257

Chen, N., Roll, R., & Ross, S. (1986). "Economic Forces and the Stock Market", *The Journal of Business,* vol. 59, pp. 383-403

Chevallier, J., Nguyen, D., Siverskog, J., & Uddin, G. (2017). "Market Integration and Financial Linkages Among Stock Markets in Pacific-Basin Countries", *Journal of Empirical Finance,* vol. 46, pp. 77-92

Collier, P. (2017). "The Downside of Globalisation: Why It Matters and What Can Be Done About It", *The World Economy,* vol. 41, pp. 967-974

CSINDEX (2018). Indices – China Securities, Available Online: http://www.csindex.com.cn/en/indices/index [Accessed 27 May, 2018]

Dent, C. (2017). "East Asian Integration Towards an East Asian Economic Community", *ADBI Working Paper Series,* no. 665, pp. 1-44

Dornbusch, R., & Fischer, S., (1980). "Exchange Rates and the Current Account", *The American Economic Review*, vol. 70(5), pp. 960 - 971, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 13 April 2018]

Economidou, C., & Murshid, A.P., (2008). "Testing the linkages between Trade and Productivity Growth", *Review of Development Economics*, vol. 12(4), pp. 845 – 860, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 13 April 2018]

Edison, H., Levine, R., Ricci, L., & Sløk, T. (2002). "International Financial Integration and Economic Growth", *National Bureau of Economic Research,* NBER Working Paper No. 9164, pp. 1-38

Enders, W., (2015). "Applied Econometric Time Series", n.p.: Hoboken, N.J.: Wiley, pp.135-136

Engle, R., & Granger, C., (1987). "Co-integration and error correction: Representation, estimation and testing", *Econometrica*, vol. 55(2), pp. 251–276

Fama, E. (1981). "Stock Returns, Real Activity, Inflation and Money", *The American Economic Review,* vol. 71, pp. 545-565

Feltenstein, A., & Nsouli, S. (2003). ""Big Bang" Versus Gradualism in Economic Reforms: An Intertemporal Analysis with an Application to China", *IMF Staff Papers,* vol. 50, pp. 458-480

Ferguson, N., & Schularick, M. (2007). ""Chimerica" and the Global Asset Market Boom", *International Finance,* vol. 10(3), pp. 215-239

Ferguson, N., & Schularick, M. (2011). "The End of Chimerica", *International Finance,* vol. 14(1), pp. 1-26

Forbes, K., & Chinn, M. (2003). "A Decomposition of Global Linkages in Financial Markets Over Time", *National Bureau of Economic Research,* no. 9555, pp. 1-51

Goh, J., Jiang, F., Tu, J., & Wang, Y. (2012). "Can U.S. Economic Variables Predict the Chinese Stock Market?", *Pacific-Basin Finance Journal,* vol. 22, pp. 69-87

Greeven, M. (2006). "The New Great Leap: The Rise of China's ICT Industry", *China's Economy in the 21st Century: Enterprise and Business Behaviour,* London: Edward Elgar

Guo, K., & N'Diaye, P. (2009). "Is China's Export-Oriented Growth Sustainable?", *IMF Working Paper Series,* no. 172, pp. 1-21

Hung, N. (2016). "Development and Impact of Chinese Investment in EU", *Creative and Knowledge Society,* vol. 6(1), pp. 1-14

Hurley, D., (2009). "A VAR Analysis of US-China Economic Linkages", *International Business & Research Journal*, vol. 8(7), pp. 69 – 80, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 15 April 2018]

Huyghebaert, N., and Wang, L. (2009). "The Co-movements of Stock Markets in East Asia: Did the 1997-1998 Asian Financial Crisis Really Strengthen Stock Market Integration", *China Economic Review,* vol. 21(1), pp. 98-112

Jarreau, J., & Poncet, S., (2012). "Export Sophistication and Economic Growth: Evidence from China", *Journal of Development Economics*, vol. 97(2), pp. 281 – 292, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 13 April 2018]

Jin, S., (2003). "The dynamics of the real interest rate, real exchange rate and the balance of payments in China: 1980-2002", *IMF Working Paper*, vol. 45(3), pp. 142-154

Johansen, S., (1991). “Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models”, *Econometrica*, vol. 59(6), pp. 1551–1580

Kasi, I., Wagan, H., & Akbar, F. (2012). ”The Changing International Transmission of U.S. Monetary Policy Shocks: Is There Evidence of Contagion Effect on OECD Countries”, *Economic Modelling,* vol. 30, pp. 90-116

Kholodilin, K., Montagnoli, A., Napolitano, O., & Siliverstovs, B. (2009). “Assessing the Impact of the ECB’s Monetary Policy on the Stock Markets: A Sectorial View”, *Economics Letters,* vol. 105, pp. 211-213

Laopodis, N., (2012). “Monetary Policy and Stock Market Dynamics Across Monetary Regimes”, *Journal of International Money and Finance,* vol. 33, pp. 381-406

Law, S., Tan, Hui., & Azman-Saini, W. (2014). “Financial Development and Income Inequality at Different Levels of Institutional Quality”, *Emerging Markets, Finance and Trade,* vol. 50, pp. 21-33

Levinger, H., & Hansakul, S. (2016). “China and the EU: Where Next in Bilateral Trade and Investment Relations?”, *China-EU Law Journal,* vol. 5(2), pp. 55-71

Lu, M. & Zhang, Z., (2003). “Exchange rate reform and its inflationary consequences: an empirical analysis for China”, *Applied Economics*, vol. 35(3), pp. 189-199

Meric, I., Ratner, M., & Meric, G. (2005). “Co-movements of Sector Index Returns in the World’s Major Stock Markets in Bull and Bear Markets: Portfolio Diversification Implications”, *International Review of Financial Analysis,* vol. 17(1), pp. 156-177

Mishkin, F. (1996). “The Channels of Monetary Transmissions: Lessons for Monetary Policy”, *National Bureau of Economic Research,* no. 5464, pp. 1-27

Narayan, S., & Narayan, P. (2012). “Does U.S. Macroeconomic Conditions Affect Asian Stock Markets? *Journal of Asian Economics,* vol. 23, pp. 669-679

Nasseh, A., & Strauss, J. (2000). “Stock Prices and Domestic and International Macroeconomic Activity: A Cointegration Approach”, *The Quarterly Review of Economics and Finance,* vol. 40, pp. 229-245

Nasser, O., and Hajilee, M. (2016). “Integration of Emerging Stock Markets with Global Stock Markets”, *Research in International Business and Finance,* vol. 36, pp. 1-12

Nikkinen, J., & Sahlström, P. (2004). "Scheduled Domestic and Macroeconomic News and Stock Valuation in Europe", *Journal of Multinational Financial Management,* vol. 14, pp. 201-215

Paramati, R.S., Gupta, R., & Hui, A., (2016). "TRADE AND INVESTMENT LINKAGES AND STOCK MARKET LONG-RUN REALTIONSHIP", *Australian Economic Papers*, vol 24(5), pp. 151- 169, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 13 April 2018]

Rigobon, R., & Sack, B. (2002). "The Impact of Monetary Policy on Asset Prices", *National Bureau of Economic Review,* no. 8794, pp. 1-36

Roll, R., & Ross, S. (1980). "An Empirical Investigation of the Arbitrage Pricing Theory", *The Journal of Finance,* vol. 35, pp. 1073-1103

Ross, S. (1976). "The Arbitrage Theory of Capital Asset Pricing", *Journal of Economic Theory,* vol. 13, pp. 341-360

Schott, P. K., (2008)." The Relative Sophistication of Chinese Exports", *Economic Policy*, vol. 23(53), pp. 5 – 49, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 13 April 2018]

Shen, P., Li, W., Wang, X., & Su, C. (2015). "Contagion Effect of the European Financial Crisis on China's Stock Markets: Interdependence and Pure Contagion", *Economic Modelling,* vol. 50, pp. 193-199

U.S. Department of Commerce (2017). China – Mining and Materials, Available Online: https://www.export.gov/article?id=China-Mining-and-Materials [Accessed 22 May 2018]

Valente, G. (2009). "International Interest Rates and U.S. Monetary Policy Announcements: Evidence from Hongkong and Singapore", *Journal of International Money and Finance,* vol. 28(6), pp. 920-940

11-5 Value of Imports and Exports by Country (Region) of Origin/Destination (2016), China Statistical Yearbook (2017), Available through: National Bureau of Statistics of China

Valukonis, M., (2013). "Chinas Stock Market Trends and Their Determinants Analysis Using Market Indices", *Economic & Management*, vol. 18(4), pp. 651 – 660, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 14 April 2018]

Wang, Y., & Tsai, J., (2014). "The Impact of Volatility Index on China's Stock Market", *Journal of Business & Economics*, vol. 6(1), pp. 23 – 46, Available through: LUSEM Library website http://www.lusem.lu.se/library [Accessed 14 April 2018]

World Bank. (2016). "Industry, Value Added, (% of GDP)", *World Bank National Accounts Data*

World Bank (2017). Trade (% of GDP), *World Bank National Accounts Data*

Xu, Y., (2000). "China's exchange rate policy", *China Economic Review*, vol. 11(3), pp. 262-277

Yang, L., & Hamori, S. (2013). "Dependence Structure Among International Stock Markets: A Garch-copula Analysis", *Applied Financial Economics,* vol. 23, pp. 1805-1817

Yongding, Y. (2010). "The Impact of the Global Financial Crisis on the Chinese Economy and China's Policy Responses", *Third World Network,* pp. 1-41

Zhang, Z., (2001). "Real exchange rates misalignment in China: an empirical investigation", *Comparative Economics*, vol. 29(2), pp. 80-94

APPENDIX

Graph 1 Impulse Responses of Shanghai Composite Index (US)

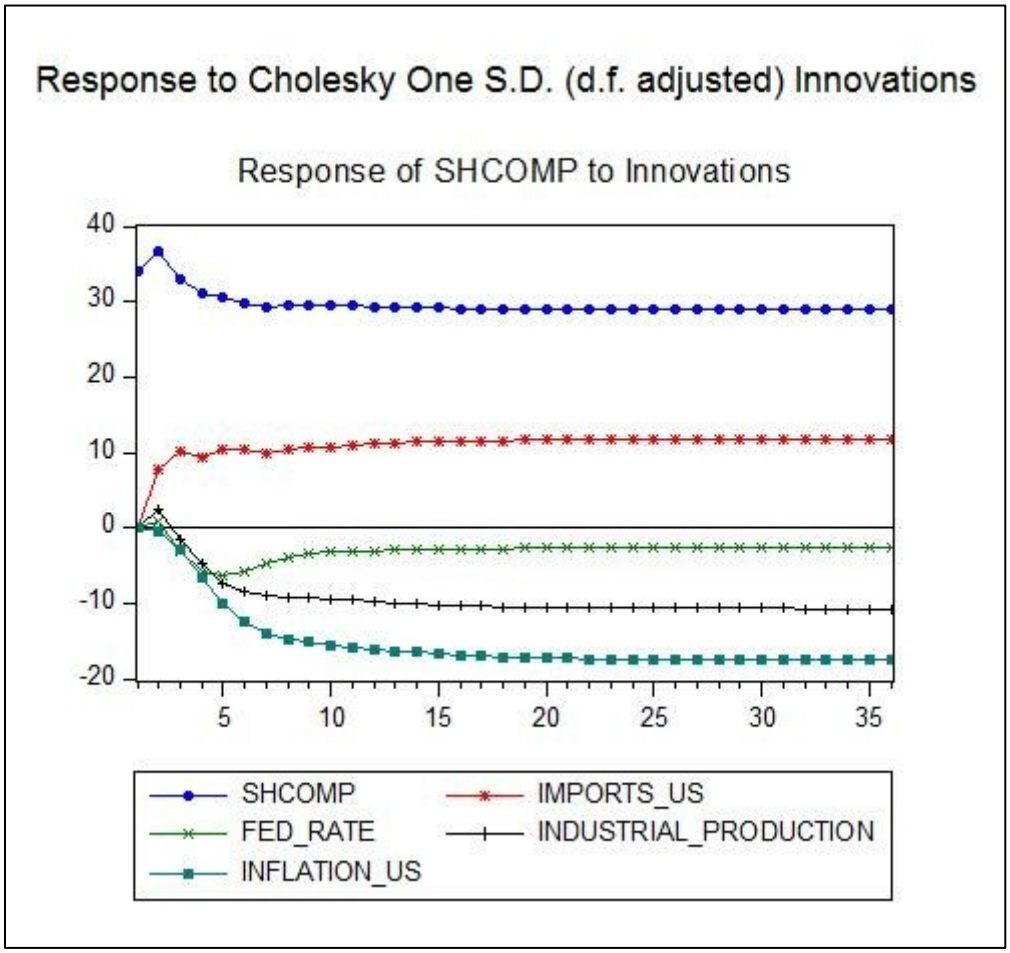

Table 1 Variance Decomposition of Shanghai Composite Index (US)

Variance Decomposition of SHCOMP:

Period	SHCOMP	IMPORTS_US	FED_RATE	INDUSTRIA	INFLATION_
1	100.00	0.00	0.00	0.00	0.00
6	85.89	6.28	1.58	2.10	4.16
12	75.63	7.51	1.26	4.48	11.12
24	68.01	8.63	0.89	6.23	16.24
36	65.14	9.05	0.75	6.89	18.17

Graph 2 Impulse Responses of Shanghai Composite Index (EU)

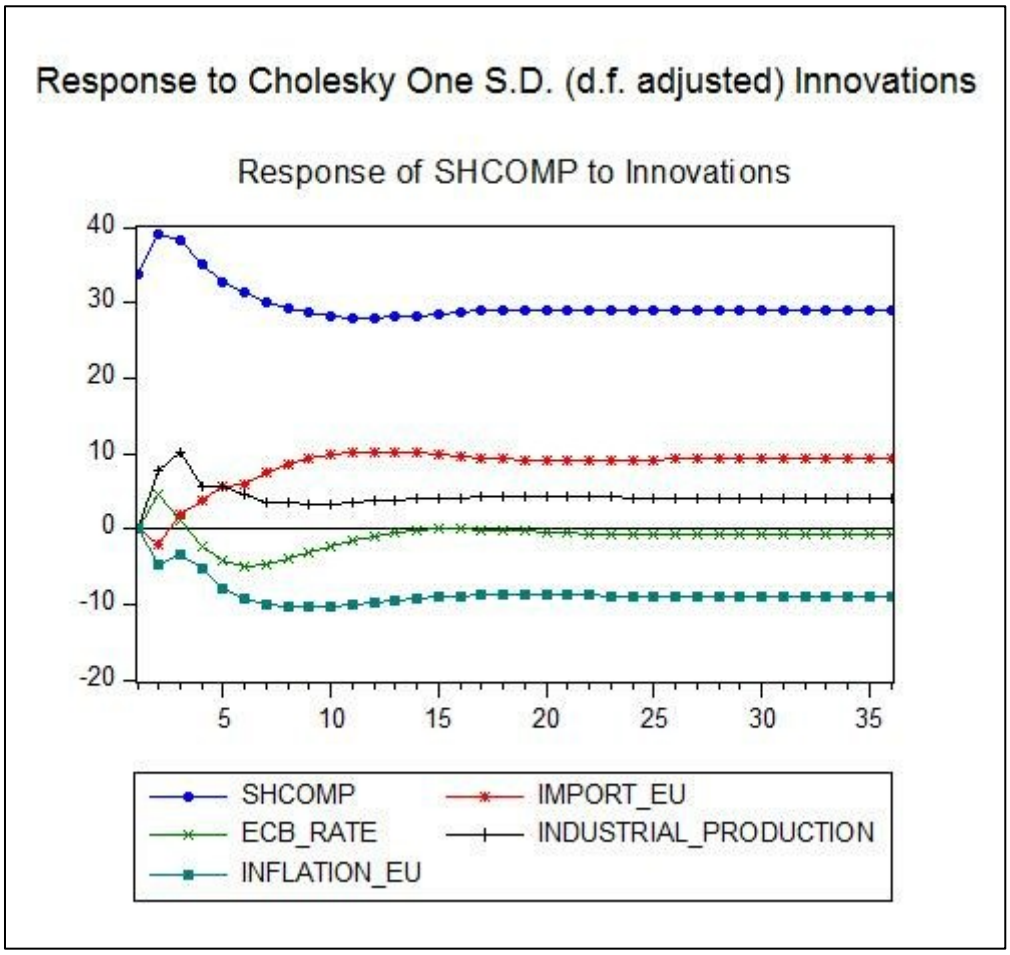

Table 2 Variance Decomposition of Shanghai Composite Index (EU)

Variance Decomposition of SHCOMP:

Period	SHCOMP	IMPORT_EU	ECB_RATE	INDUSTRIA	INFLATION_
1	100.00	0.00	0.00	0.00	0.00
6	92.32	1.12	0.89	3.04	2.62
12	86.82	4.29	0.90	2.21	5.78
24	84.47	6.35	0.49	1.97	6.72
36	83.72	6.99	0.35	1.87	7.07

Graph 3 Impulse Responses of CSI 300 Informationtech (US)

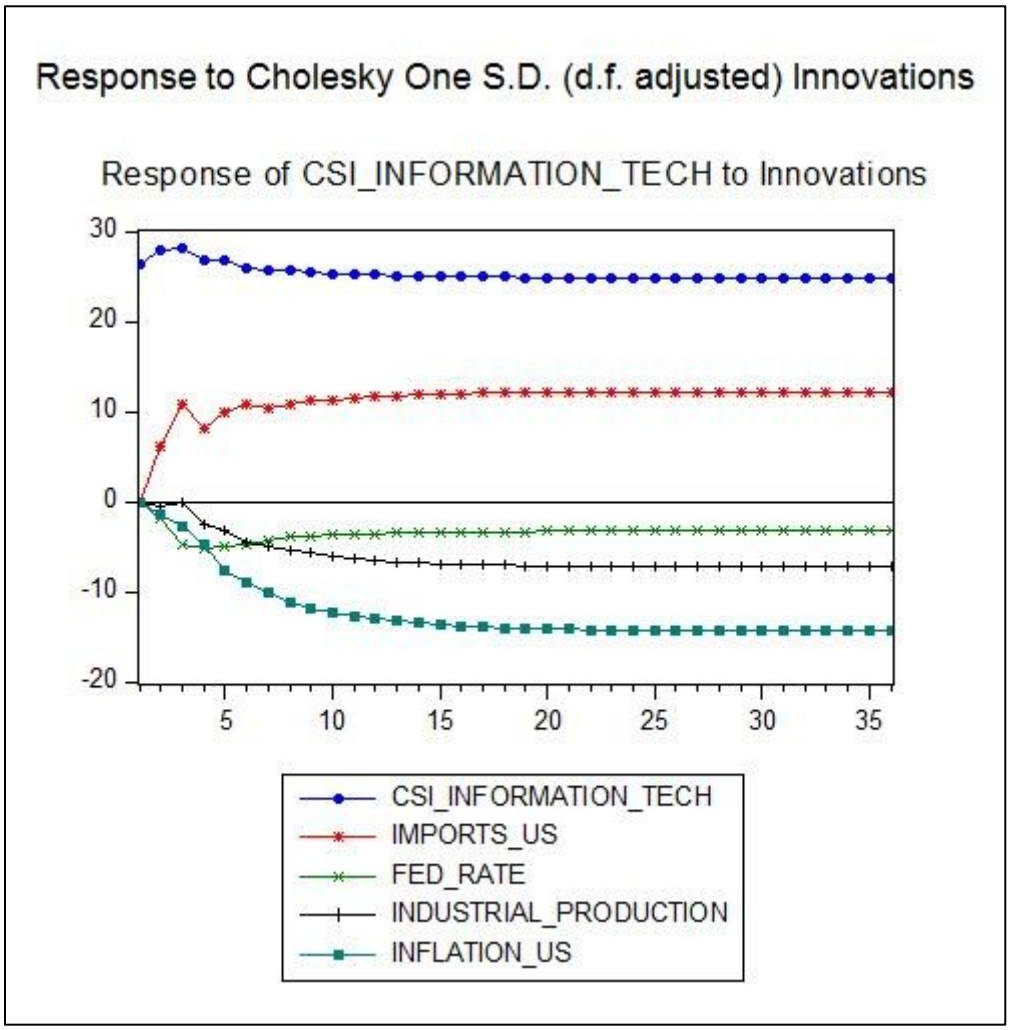

Table 3 Variance Decomposition of CSI 300 Informationtech (US)

Variance Decomposition of CSI_INFORMATION_TECH:

Period	CSI_INFOR	IMPORTS_US	FED_RATE	INDUSTRIA	INFLATION_
1	100.00	0.00	0.00	0.00	0.00
6	85.38	8.50	1.97	0.73	3.41
12	75.73	10.86	1.74	2.25	9.42
24	67.79	12.60	1.41	3.65	14.54
36	64.91	13.21	1.28	4.17	16.43

Graph 4 Impulse Responses of CSI 300 Informationtech (EU)

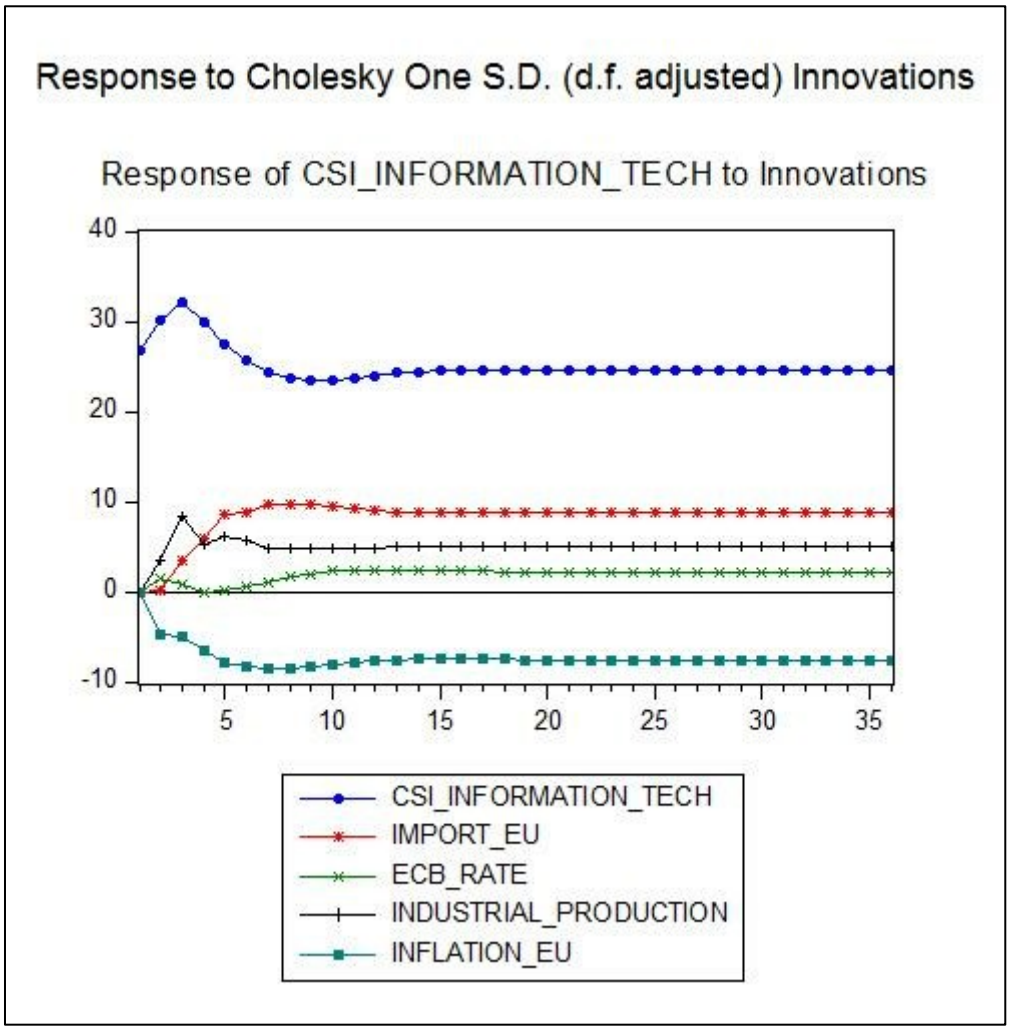

Table 4 Variance Decomposition of CSI 300 Informationtech (EU)

Variance Decomposition of CSI_INFORMATION_TECH:

Period	CSI_INFOR	IMPORT_EU	ECB_RATE	INDUSTRIA	INFLATION_
1	100.00	0.00	0.00	0.00	0.00
6	89.20	3.51	0.05	3.22	4.02
12	83.12	7.26	0.27	3.14	6.20
24	80.99	8.56	0.45	3.19	6.81
36	80.20	9.03	0.51	3.21	7.04

Graph 5 Impulse Responses of CSI 300 Materials (US)

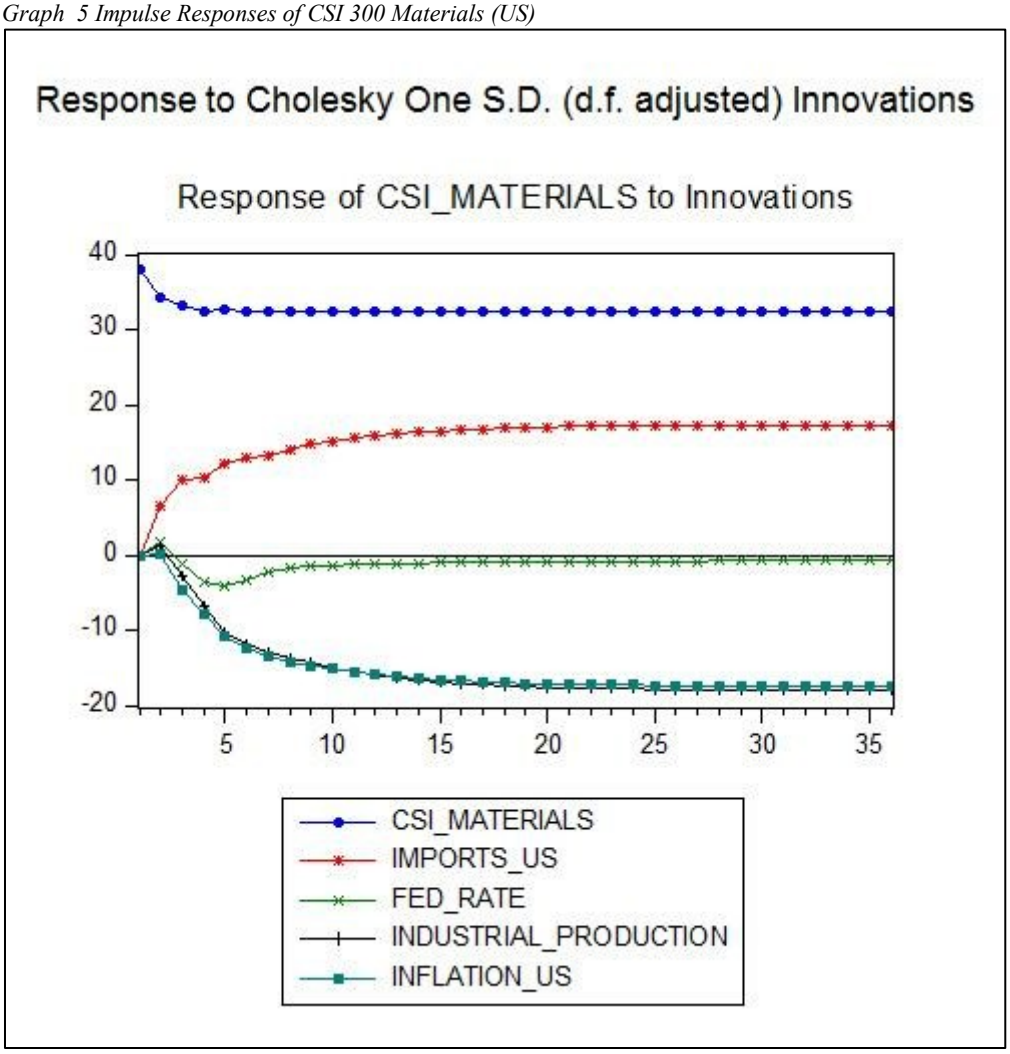

Table 5 Variance Decomposition of CSI 300 Materials (US)

Variance Decomposition of CSI_MATERIALS:

Period	CSI_MATERI	IMPORTS_US	FED_RATE	INDUSTRIA	INFLATION_
1	100.00	0.00	0.00	0.00	0.00
6	84.49	6.90	0.55	3.74	4.33
12	71.77	10.15	0.33	8.59	9.16
24	62.28	12.68	0.17	12.51	12.35
36	58.96	13.56	0.12	13.91	13.44

Graph 6 Impulse Responses of CSI 300 Materials (EU)

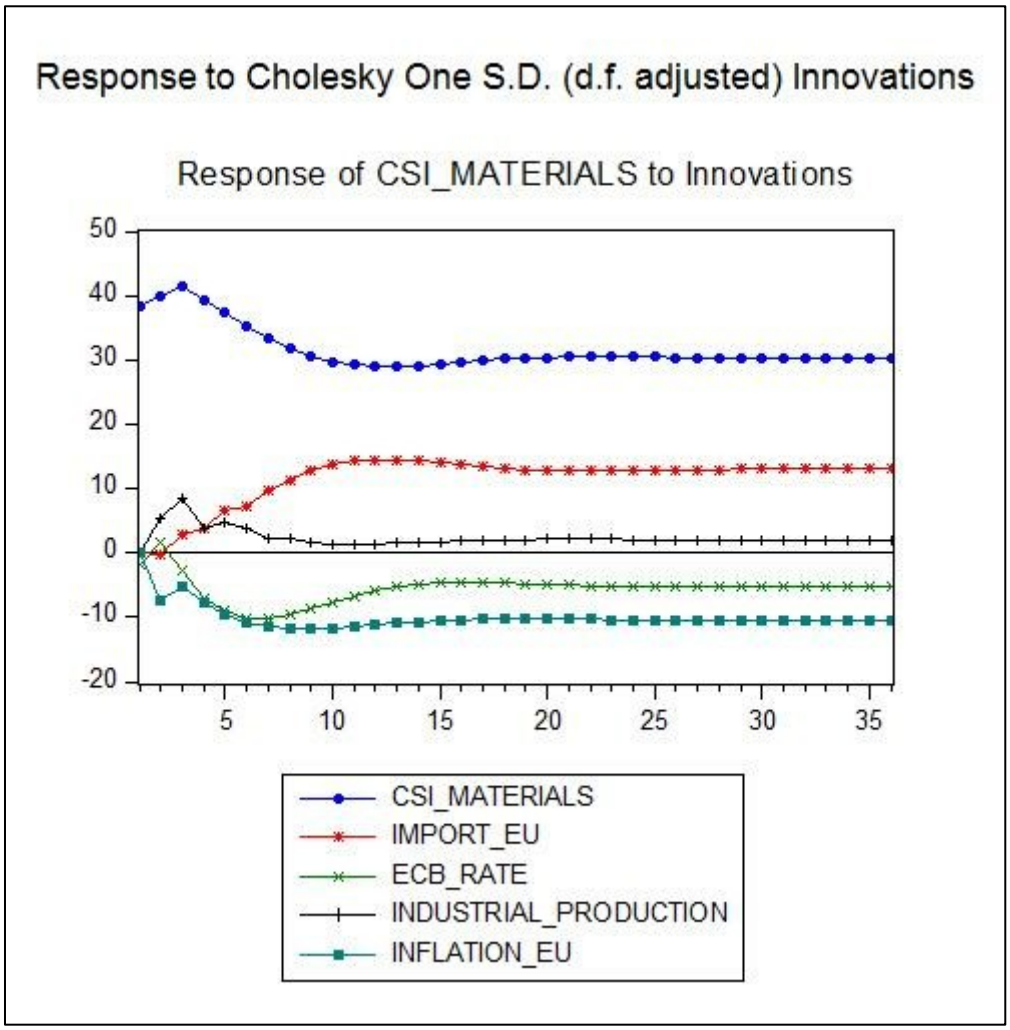

Table 6 Variance Decomposition of CSI 300 Materials (EU)

Variance Decomposition of CSI_MATERIALS:

Period	CSI_MATERI	IMPORT_EU	ECB_RATE	INDUSTRIA	INFLATION_
1	99.79	0.00	0.21	0.00	0.00
6	91.20	1.19	2.54	1.56	3.51
12	82.54	6.25	3.70	0.98	6.53
24	78.73	10.04	2.92	0.68	7.63
36	77.49	11.19	2.71	0.57	8.03

Graph 7 Impulse Responses of CSI 300 Industrial Production (US)

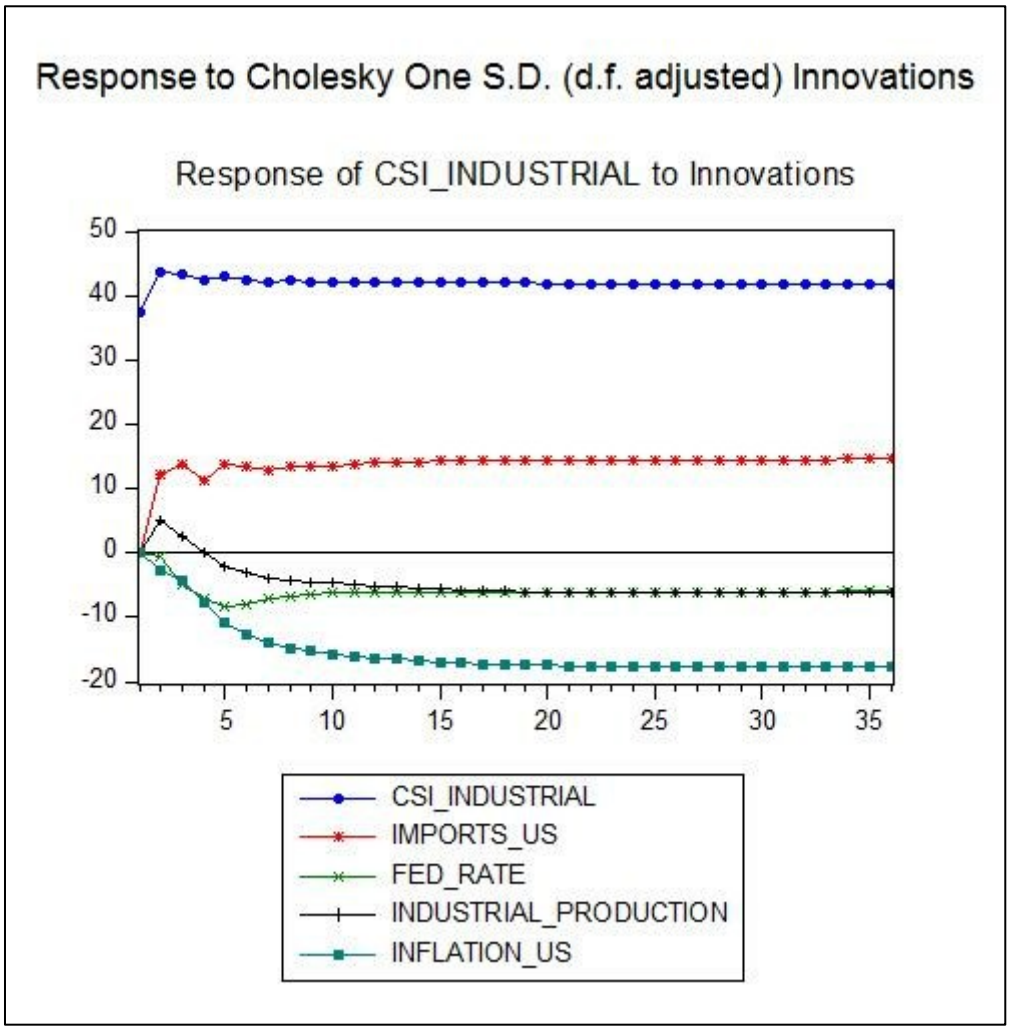

Table 7 Variance Decomposition of CSI 300 Industrial Production (US)

Variance Decomposition of CSI_INDUSTRIAL:

Period	CSI_INDUS	IMPORTS_US	FED_RATE	INDUSTRIA	INFLATION_
1	100.00	0.00	0.00	0.00	0.00
6	88.04	6.87	1.73	0.38	2.98
12	83.04	7.52	1.80	0.67	6.97
24	79.01	8.20	1.69	1.10	10.01
36	77.43	8.46	1.63	1.30	11.18

Graph 8 Impulse Responses of CSI 300 Inustrial Production (EU)

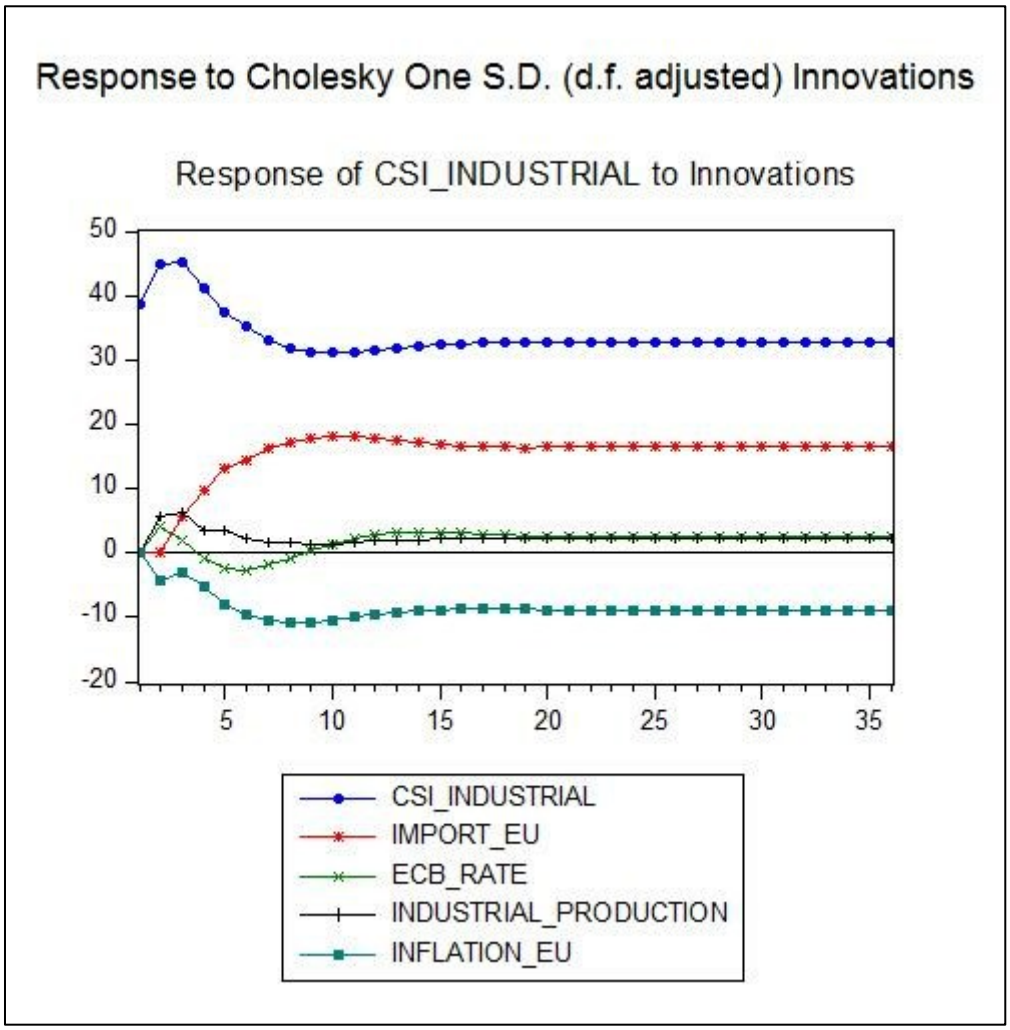

Table 8 Variance Decomposition of CSI 300 Industrial Production (EU)

Variance Decomposition of CSI_INDUSTRIAL:

Period	CSI_INDUS	IMPORT_EU	ECB_RATE	INDUSTRIA	INFLATION_
1	100.00	0.00	0.00	0.00	0.00
6	92.02	4.72	0.34	0.94	1.99
12	82.40	12.26	0.28	0.60	4.46
24	78.52	15.64	0.40	0.47	4.96
36	77.18	16.81	0.41	0.43	5.17

Table 9 Vector Error Model Parameter Estimates of Shanghai Composite Index (US)

Cointegrating Eq:	CointEq1				
SHCOMP(-1)	1.00				
D_IMPORTS_US(-1)	-0.06***				
FED_RATE(-1)	-34.49				
INDUSTRIAL_PRODUCT	43.86***				
INFLATION_US(-1)	70.84***				
C	-2913.03				
Error Correction:	**D(SHCOMP)**	**D(IMPORTS_US)**	**D(FED_RATE)**	**D(INDUSTRIA**	**D(INFLATION**
CointEq1	-0.07***	2.26**	-0.00***	-0.00	-0.00
D(SHCOMP(-1))	0.12	-10.58**	0.00	-0.00	0.00***
D(SHCOMP(-2))	-0.07	-1.86	0.00	0.00	-0.00
D(D_IMPORTS_US(-1))	0.00	-0.63***	-0.00	-0.00	-0.00
D(D_IMPORTS_US(-2))	0.00	-0.39***	0.00	0.00	-0.00
D(FED_RATE(-1))	11.08	2373.45	0.64***	-0.64	1.41***
D(FED_RATE(-2))	-64.13*	2581.11	-0.27***	1.34	-1.51***
D(INDUSTRIAL_PRODU	3.72	71.22	0.02***	-0.30***	0.04
D(INDUSTRIAL_PRODU	-0.21	74.52	0.00	0.12	0.04
D(INFLATION_US(-1))	3.29	526.00	0.02	0.31	0.52***
D(INFLATION_US(-2))	-3.77	-648.76	0.01	0.28	-0.01
C	-1.52	370.84**	-0.01	0.07	-0.02
R-squared	0.17	0.49	0.59	0.20	0.43
Adj. R-squared	0.09	0.43	0.55	0.12	0.37
F-statistic	1.14	2.71**	2.1**	1.00	3.57***

Notes:

The LM test for autocorrelation was performed on the model and no residual autocorrelation was found at 5% significance level.

CointEq1 refers to the error correction mechanism that is normalized with respect to each variable.

****, ** and * refers to the rejection of the null hypothesis of no causality at 1%, 5%, and 10% significance level, respectively.*

Table 10 Vector Error Model Parameter Estimates of Shanghai Composite Index (EU)

Cointegrating Eq:	CointEq1				
SHCOMP(-1)	1.00				
IMPORT_EU(-1)	-0.08***				
ECB_RATE(-1)	-138.81***				
INDUSTRIAL_PRODUCT	-1.86				
INFLATION_EU(-1)	126.59**				
C	2058.78				
Error Correction:	**D(SHCOMP)**	**D(IMPORT_E**	**D(ECB_RATE)**	**D(INDUSTRIA**	**D(INFLATION**
CointEq1	-0.02**	4.10***	0.00**	0.00***	0.00***
D(SHCOMP(-1))	0.18**	-12.55**	0.00**	0.00	0.00
D(SHCOMP(-2))	-0.08	-7.31	-0.00	-0.01	0.00
D(IMPORT_EU(-1))	-0.00**	-0.18*	0.00**	0.00	0.00
D(IMPORT_EU(-2))	0.00	0.01	0.00	0.00*	0.00
D(ECB_RATE(-1))	61.91*	3740.15	0.73***	0.68	0.02
D(ECB_RATE(-2))	-102.23***	692.38	-0.10	3.95**	0.03
D(INDUSTRIAL_PRODU	3.37**	104.18	0.00**	-0.52***	0.02
D(INDUSTRIAL_PRODU	2.62*	47.12	-0.00	-0.26***	0.03**
D(INFLATION_EU(-1))	-14.71	-836.45	0.15***	0.81	0.15
D(INFLATION_EU(-2))	-2.52	-1103.46	-0.00	-0.04	0.05
C	-2.05	223.00	-0.02**	0.35*	-0.01
R-squared	0.19	0.29	0.72	0.33	0.18
Adj. R-squared	0.10	0.21	0.69	0.26	0.09
F-statistic	2.57**	1.87*	4.36***	3.10***	1.98**

Notes:

The LM test for autocorrelation was performed on the model and no residual autocorrelation was found at 5% significance level.

CointEq1 refers to the error correction mechanism that is normalized with respect to each variable.

****, ** and * refers to the rejection of the null hypothesis of no causality at 1%, 5%, and 10% significance level, respectively.*

Table 11 Vector Error Model Parameter Estimates of CSI 300 Informationtech (US)

Cointegrating Eq:	CointEq1				
CSI_INFORMATION_TE	1.00				
IMPORTS_US(-1)	-0.04***				
FED_RATE(-1)	-14.41				
INDUSTRIAL_PRODUCT	28.32***				
INFLATION_US(-1)	47.24***				
C	-1738.25				
Error Correction:	**D(CSI_INFO**	**D(IMPORTS_**	**D(FED_RATE)**	**D(INDUSTRIA**	**D(INFLATION**
CointEq1	-0.08***	3.91**	-0.00***	-0.00	-0.00
D(CSI_INFORMATION_T	0.08	-11.12*	0.00*	0.00	0.00**
D(CSI_INFORMATION_T	0.10	3.42	0.00	-0.00	-0.00
D(IMPORTS_US(-1))	0.00	-0.62***	-0.00	-0.00	-0.00
D(IMPORTS_US(-2))	0.00*	-0.39***	-0.00	-0.00	-0.00
D(FED_RATE(-1))	-21.44	1775.37	0.66***	-0.44	1.59***
D(FED_RATE(-2))	-20.81	2848.19	-0.27***	1.36	-1.58***
D(INDUSTRIAL_PRODU	1.43	83.75	0.02***	-0.26**	0.04
D(INDUSTRIAL_PRODU	1.74	96.89	0.00	0.10	0.04
D(INFLATION_US(-1))	0.16	481.68	0.02	0.41	0.52
D(INFLATION_US(-2))	-0.22	-616.24	0.01	0.20	-0.02
C	-0.76	373.10**	-0.01	0.08	-0.02
R-squared	0.19	0.48	0.59	0.19	0.43
Adj. R-squared	0.11	0.43	0.55	0.11	0.37
F-statistic	0.95	2.49**	2.16**	0.95	3.46***

Notes:

The LM test for autocorrelation was performed on the model and no residual autocorrelation was found at 5% significance level.

CointEq1 refers to the error correction mechanism that is normalized with respect to each variable.

****, ** and * refers to the rejection of the null hypothesis of no causality at 1%, 5%, and 10% significance level, respectively.*

Table 12 Vector Error Model Parameter Estimates of CSI 300 Informationtech (EU)

Cointegrating Eq:	CointEq1				
CSI_INFORMATION_TE	1.00				
IMPORT_EU(-1)	-0.03***				
ECB_RATE(-1)	-51.62***				
INDUSTRIAL_PRODUCT	-4.12				
INFLATION_EU(-1)	77.40***				
C	903.85				
Error Correction:	**D(CSI_INFO**	**D(IMPORT_E**	**D(ECB_RATE)**	**D(INDUSTRIA**	**D(INFLATION**
CointEq1	-0.07**	10.83***	0.00***	0.00***	0.00
D(CSI_INFORMATION_T	0.18*	-20.50**	0.00	0.00	0.00
D(CSI_INFORMATION_T	0.10	-5.24	-0.00	-0.01	0.00
D(IMPORT_EU(-1))	-0.00*	-0.16	0.00**	0.00	0.00
D(IMPORT_EU(-2))	-0.00	0.03	0.00	0.00*	0.00
D(ECB_RATE(-1))	24.51	2650.52	0.69***	0.32	0.01
D(ECB_RATE(-2))	-38.60	259.04	-0.10	3.39*	0.02
D(INDUSTRIAL_PRODU	1.33	161.22	0.01**	-0.49***	0.02
D(INDUSTRIAL_PRODU	2.96**	87.16	0.00	-0.22**	0.03**
D(INFLATION_EU(-1))	-12.80	-1047.44	0.13***	0.56	0.14
D(INFLATION_EU(-2))	2.45	-1110.50	-0.01	0.03	0.03
C	-0.39	160.38	-0.02**	0.31	-0.02
R-squared	0.16	0.27	0.72	0.31	0.16
Adj. R-squared	0.07	0.20	0.69	0.24	0.08
F-statistic	1.59	1.83*	3.68***	2.41**	1.75*

Notes:

The LM test for autocorrelation was performed on the model and no residual autocorrelation was found at 5% significance level.

CointEq1 refers to the error correction mechanism that is normalized with respect to each variable.

****, ** and * refers to the rejection of the null hypothesis of no causality at 1%, 5%, and 10% significance level, respectively.*

Table 13 Vector Error Model Parameter Estimates of CSI 300 Materials (US)

Cointegrating Eq:	CointEq1				
CSI_MATERIALS(-1)	1.00				
IMPORTS_US(-1)	-0.08***				
FED_RATE(-1)	-14.59				
INDUSTRIAL_PRODUCT	83.58***				
INFLATION_US(-1)	44.37				
C	-5849.55				
Error Correction:	**D(CSI_MATER**	**D(IMPORTS_**	**D(FED_RATE)**	**D(INDUSTRIA**	**D(INFLATION**
CointEq1	-0.06***	1.63**	-0.00***	-0.00*	-0.00
D(CSI_MATERIALS(-1))	-0.06	-6.57	0.00	-0.00	0.00***
D(CSI_MATERIALS(-2))	-0.03	-0.31	0.00	-0.00	-0.00
D(IMPORTS_US(-1))	-0.00	-0.63***	-0.00	-0.00	-0.00
D(IMPORTS_US(-2))	0.00	-0.40***	-0.00	-0.00	0.00
D(FED_RATE(-1))	22.68	2005.57	0.65***	-0.83	1.56***
D(FED_RATE(-2))	-43.19	2831.80	-0.29***	1.03	-1.52***
D(INDUSTRIAL_PRODU	4.72*	72.84	0.02***	-0.25**	0.03
D(INDUSTRIAL_PRODU	0.68	80.91	0.00	0.12	0.04
D(INFLATION_US(-1))	2.69	557.69	0.02	0.44	0.50***
D(INFLATION_US(-2))	-12.83	-552.11	0.00	0.21	-0.02
C	-2.73	365.77**	-0.01	0.06	-0.02
R-squared	0.17	0.48	0.59	0.21	0.42
Adj. R-squared	0.08	0.42	0.55	0.12	0.36
F-statistic	1.01	2.30**	2.10**	0.76	3.46***

Notes:

The LM test for autocorrelation was performed on the model and no residual autocorrelation was found at 5% significance level.

CointEq1 refers to the error correction mechanism that is normalized with respect to each variable.

****, ** and * refers to the rejection of the null hypothesis of no causality at 1%, 5%, and 10% significance level, respectively.*

Table 14 Vector Error Model Parameter Estimates of CSI 300 Materials (EU)

Cointegrating Eq:	CointEq1				
CSI_MATERIALS(-1)	1.00				
IMPORT_EU(-1)	-0.05***				
ECB_RATE(-1)	-83.28**				
INDUSTRIAL_PRODUCT	12.60				
INFLATION_EU(-1)	18.69				
C	102.28				
Error Correction:	**D(CSI_MATER**	**D(IMPORT_E**	**D(ECB_RATE)**	**D(INDUSTRIA**	**D(INFLATION_**
CointEq1	-0.03**	6.08***	0.00***	0.00***	0.00*
D(CSI_MATERIALS(-1))	0.06	-11.99**	0.00*	0.00	0.00
D(CSI_MATERIALS(-2))	0.06	-8.12	-0.00	0.00	0.00
D(IMPORT_EU(-1))	-0.00	-0.16	0.00**	0.00	0.00**
D(IMPORT_EU(-2))	0.00	0.03	0.00	0.00*	0.00
D(ECB_RATE(-1))	52.56	3348.71	0.73***	0.58	0.02
D(ECB_RATE(-2))	-104.71***	170.15	-0.11	3.79*	0.06
D(INDUSTRIAL_PRODU	2.73	49.35	0.01	-0.56***	0.01
D(INDUSTRIAL_PRODU	3.16*	6.73	-0.00	-0.27***	0.02*
D(INFLATION_EU(-1))	-28.44**	-832.78	0.14***	0.66	0.12
D(INFLATION_EU(-2))	4.52	-1100.50	-0.00	0.15	0.03
C	-4.11	154.80	-0.02*	0.36*	-0.01
R-squared	0.15	0.29	0.72	0.31	0.19
Adj. R-squared	0.06	0.22	0.69	0.24	0.11
F-statistic	2.21**	1.60	3.84***	2.64**	1.87*

Notes:

The LM test for autocorrelation was performed on the model and no residual autocorrelation was found at 5% significance level.

CointEq1 refers to the error correction mechanism that is normalized with respect to each variable.

****, ** and * refers to the rejection of the null hypothesis of no causality at 1%, 5%, and 10% significance level, respectively.*

Table 15 Vector Error Model Parameter Estimates of CSI 300 Industrial Production (US)

Cointegrating Eq:	CointEq1				
CSI_INDUSTRIAL(-1)	1.00				
IMPORTS_US(-1)	-0.07***				
FED_RATE(-1)	25.22				
INDUSTRIAL_PRODUCT	60.35***				
INFLATION_US(-1)	86.70***				
C	-3960.35				
Error Correction:	**D(CSI_INDU**	**D(IMPORTS_**	**D(FED_RATE)**	**D(INDUSTRIA**	**D(INFLATION**
CointEq1	-0.04**	1.45*	-0.00***	-0.00*	-0.00
D(CSI_INDUSTRIAL(-1))	0.15	-7.29	0.00	-0.00	0.00**
D(CSI_INDUSTRIAL(-2))	0.03	-1.51	0.00	0.00	-0.00
D(IMPORTS_US(-1))	0.00**	-0.65***	-0.00	-0.00	-0.00
D(IMPORTS_US(-2))	0.00	-0.39***	0.00	0.00	-0.00
D(FED_RATE(-1))	9.22	2159.86	0.65***	-0.54	1.41***
D(FED_RATE(-2))	-64.88*	2414.47	-0.28***	1.24	-1.52***
D(INDUSTRIAL_PRODU	4.33	93.02	0.01***	-0.32***	0.04
D(INDUSTRIAL_PRODU	0.37	85.55	0.00	0.11	0.04
D(INFLATION_US(-1))	-3.57	569.27	0.02	0.32	0.52***
D(INFLATION_US(-2))	-2.31	-597.38	0.01	0.26	-0.01
C	-2.94	361.27**	-0.01	0.06	-0.02
R-squared	0.21	0.47	0.60	0.21	0.42
Adj. R-squared	0.12	0.42	0.56	0.13	0.36
F-statistic	1.62	2.38**	1.83*	0.97	3.17***

Notes:

The LM test for autocorrelation was performed on the model and no residual autocorrelation was found at 5% significance level.

CointEq1 refers to the error correction mechanism that is normalized with respect to each variable.

****, ** and * refers to the rejection of the null hypothesis of no causality at 1%, 5%, and 10% significance level, respectively.*

Table 16 Vector Error Model Parameter Estimates of CSI 300 Industrial Production (EU)

Cointegrating Eq:	CointEq1				
CSI_INDUSTRIAL(-1)	1.00				
IMPORT_EU(-1)	-0.08***				
ECB_RATE(-1)	-134.81***				
INDUSTRIAL_PRODUCT	5.58				
INFLATION_EU(-1)	128.12**				
C	1485.80				
Error Correction:	**D(CSI_INDU**	**D(IMPORT_E**	**D(ECB_RATE)**	**D(INDUSTRIA**	**D(INFLATION**
CointEq1	-0.04**	4.10***	0.00***	0.00***	0.00
D(CSI_INDUSTRIAL(-1))	0.20**	-11.92**	0.00**	0.01	0.00
D(CSI_INDUSTRIAL(-2))	-0.03	-4.28	-0.00	-0.01	0.00
D(IMPORT_EU(-1))	-0.00*	-0.17	0.00**	0.00	0.00*
D(IMPORT_EU(-2))	-0.00	0.02	0.00	0.00*	0.00
D(ECB_RATE(-1))	50.70	3285.44	0.74***	1.15	-0.01
D(ECB_RATE(-2))	-90.20**	672.20	-0.11	3.42*	0.06
D(INDUSTRIAL_PRODU	2.88*	99.57	0.01*	-0.53***	0.02
D(INDUSTRIAL_PRODU	1.48	55.67	-0.00	-0.27***	0.03**
D(INFLATION_EU(-1))	-11.36	-879.11	0.14***	0.79	0.14
D(INFLATION_EU(-2))	1.91	-981.70	-0.01	-0.07	0.04
C	-2.29	189.89	-0.02**	0.35	-0.01
R-squared	0.16	0.29	0.72	0.33	0.17
Adj. R-squared	0.07	0.22	0.69	0.26	0.08
F-statistic	1.61	1.70*	4.44***	3.16***	1.78*

Notes:

The LM test for autocorrelation was performed on the model and no residual autocorrelation was found at 5% significance level.

CointEq1 refers to the error correction mechanism that is normalized with respect to each variable.

****, ** and * refers to the rejection of the null hypothesis of no causality at 1%, 5%, and 10% significance level, respectively.*

Table 17 Johansen Cointegration Test Result of Shanghai Composite Index (US)

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.***
None*	0.27	69.17	69.82	0.06
At most 1	0.13	31.93	47.86	0.62
At most 2	0.08	15.89	29.80	0.72
At most 3	0.05	6.13	15.49	0.68
At most 4	0.01	0.72	3.84	0.40

Trace test indicates no cointegration at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.***
None **	0.27	37.24	33.88	0.02
At most 1	0.13	16.04	27.58	0.66
At most 2	0.08	9.76	21.13	0.77
At most 3	0.05	5.41	14.26	0.69
At most 4	0.01	0.72	3.84	0.40

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Table 18 Johansen Cointegration Test Results of Shanghai Composite Index (EU)

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.***
None **	0.24	79.28	69.82	0.01
At most 1	0.18	46.53	47.86	0.07
At most 2	0.10	23.81	29.80	0.21
At most 3	0.06	11.45	15.49	0.19
At most 4	0.03	3.64	3.84	0.06

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.***
None*	0.24	32.74	33.88	0.07
At most 1	0.18	22.72	27.58	0.19
At most 2	0.10	12.36	21.13	0.51
At most 3	0.06	7.81	14.26	0.40
At most 4	0.03	3.64	3.84	0.06

Max-eigenvalue test indicates no cointegration at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Table 19 Johansen Cointegration Test Result of CSI 300 Informationtech (US)

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.***
None **	0.26	74.87	69.82	0.02
At most 1	0.15	39.02	47.86	0.26
At most 2	0.11	20.48	29.80	0.39
At most 3	0.05	6.42	15.49	0.65
At most 4	0.01	0.64	3.84	0.42

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.***
None **	0.26	35.84	33.88	0.03
At most 1	0.15	18.54	27.58	0.45
At most 2	0.11	14.07	21.13	0.36
At most 3	0.05	5.77	14.26	0.64
At most 4	0.01	0.64	3.84	0.42

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Table 20 Johansen Cointegration Test Result of CSI 300 Informationtech (EU)

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.***
None **	0.26	88.07	69.82	0.00
At most 1 **	0.18	52.93	47.86	0.02
At most 2*	0.14	29.68	29.80	0.05
At most 3	0.07	12.33	15.49	0.14
At most 4*	0.03	3.35	3.84	0.07

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.***
None **	0.26	35.14	33.88	0.04
At most 1	0.18	23.25	27.58	0.16
At most 2	0.14	17.35	21.13	0.16
At most 3	0.07	8.99	14.26	0.29
At most 4*	0.03	3.35	3.84	0.07

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Table 21 Johansen Cointegration Test Result of CSI 300 Materials (US)

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.***
None **	0.25	88.80	69.82	0.00
At most 1 **	0.19	55.89	47.86	0.01
At most 2 **	0.13	31.79	29.80	0.03
At most 3*	0.09	15.08	15.49	0.06
At most 4 **	0.04	4.24	3.84	0.04

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.***
None*	0.25	32.90	33.88	0.07
At most 1	0.19	24.10	27.58	0.13
At most 2	0.13	16.71	21.13	0.19
At most 3	0.09	10.84	14.26	0.16
At most 4 **	0.04	4.24	3.84	0.04

Max-eigenvalue test indicates no cointegration at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Table 22 Johansen Cointegration Test Result of CSI 300 Materials (EU)

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.***
None **	0.27	76.18	69.82	0.01
At most 1	0.15	39.15	47.86	0.25
At most 2	0.10	19.93	29.80	0.43
At most 3	0.06	8.01	15.49	0.46
At most 4	0.01	0.71	3.84	0.40

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.***
None **	0.27	37.03	33.88	0.02
At most 1	0.15	19.22	27.58	0.40
At most 2	0.10	11.93	21.13	0.56
At most 3	0.06	7.30	14.26	0.45
At most 4	0.01	0.71	3.84	0.40

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Table 23 Johansen Cointegration Test Result of CSI 300 Industrial Production (US)

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.***
None*	0.27	67.45	69.82	0.08
At most 1	0.13	31.36	47.86	0.65
At most 2	0.08	15.08	29.80	0.77
At most 3	0.04	5.32	15.49	0.77
At most 4	0.01	0.61	3.84	0.43

Trace test indicates no cointegration at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.***
None **	0.27	36.09	33.88	0.03
At most 1	0.13	16.28	27.58	0.64
At most 2	0.08	9.77	21.13	0.77
At most 3	0.04	4.70	14.26	0.78
At most 4	0.01	0.61	3.84	0.43

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 24 Johansen Cointegration Test Result of CSI 300 Industrial Production (EU)

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.***
None **	0.25	80.29	69.82	0.01
At most 1*	0.18	46.53	47.86	0.07
At most 2	0.10	23.45	29.80	0.22
At most 3	0.06	11.02	15.49	0.21
At most 4 **	0.03	4.00	3.84	0.05

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.***
None*	0.25	33.76	33.88	0.05
At most 1	0.18	23.08	27.58	0.17
At most 2	0.10	12.43	21.13	0.51
At most 3	0.06	7.02	14.26	0.49
At most 4 **	0.03	4.00	3.84	0.05

Max-eigenvalue test indicates no cointegration at the 0.05 level
** denotes rejection of the hypothesis at the 0.05 level
* denotes rejection of the hypothesis at the 0.1 level
***MacKinnon-Haug-Michelis (1999) p-values

Table 25 VEC Granger Causality Test of Shanghai Composite Index (US)

Dependent variable: D(SHCOMP)

Excluded	Chi-sq	df	Prob.
D(IMPORTS_US)	0.32	2	0.85
D(FED_RATE)	3.78	2	0.15
D(INDUSTRIAL_PROD	2.87	2	0.24
D(INFLATION_US)	0.25	2	0.88
All	8.21	8	0.41

Dependent variable: D(IMPORTS_US)

Excluded	Chi-sq	df	Prob.
D(SHCOMP)	5.41	2	0.07
D(FED_RATE)	6.24	2	0.04
D(INDUSTRIAL_PROD	0.53	2	0.77
D(INFLATION_US)	2.88	2	0.24
All	21.65	8	0.01

Dependent variable: D(FED_RATE)

Excluded	Chi-sq	df	Prob.
D(SHCOMP)	3.66	2	0.16
D(IMPORTS_US)	3.19	2	0.20
D(INDUSTRIAL_PROD	8.60	2	0.01
D(INFLATION_US)	2.20	2	0.33
All	16.77	8	0.03

Dependent variable: D(INDUSTRIAL_PRODUCTION)

Excluded	Chi-sq	df	Prob.
D(SHCOMP)	1.09	2	0.58
D(IMPORTS_US)	0.74	2	0.69
D(FED_RATE)	0.80	2	0.67
D(INFLATION_US)	1.90	2	0.39
All	7.98	8	0.44

Dependent variable: D(INFLATION_US)

Excluded	Chi-sq	df	Prob.
D(SHCOMP)	7.47	2	0.02
D(IMPORTS_US)	0.18	2	0.91
D(FED_RATE)	15.31	2	0.00
D(INDUSTRIAL_PROD	3.19	2	0.20
All	28.54	8	0.00

Table 26 VEC Granger Causality Test of Shanghai Composite Index (EU)

Dependent variable: D(SHCOMP)

Excluded	Chi-sq	df	Prob.
D(IMPORT_EU)	4.70	2	0.10
D(ECB_RATE)	11.04	2	0.00
D(INDUSTRIAL_PROD	5.89	2	0.05
D(INFLATION_EU)	1.45	2	0.48
All	20.53	8	0.01

Dependent variable: D(IMPORT_EU)

Excluded	Chi-sq	df	Prob.
D(SHCOMP)	5.73	2	0.06
D(ECB_RATE)	5.38	2	0.07
D(INDUSTRIAL_PROD	0.92	2	0.63
D(INFLATION_EU)	2.25	2	0.00
All	14.92	8	0.06

Dependent variable: D(ECB_RATE)

Excluded	Chi-sq	df	Prob.
D(SHCOMP)	5.92	2	0.05
D(IMPORT_EU)	5.73	2	0.06
D(INDUSTRIAL_PROD	5.18	2	0.08
D(INFLATION_EU)	20.37	2	0.00
All	34.86	8	0.00

Dependent variable: D(INDUSTRIAL_PRODUCTION)

Excluded	Chi-sq	df	Prob.
D(SHCOMP)	1.29	2	0.53
D(IMPORT_EU)	3.92	2	0.14
D(ECB_RATE)	9.77	2	0.01
D(INFLATION_EU)	1.12	2	0.57
All	24.70	8	0.00

Dependent variable: D(INFLATION_EU)

Excluded	Chi-sq	df	Prob.
D(SHCOMP)	4.81	2	0.09
D(IMPORT_EU)	2.86	2	0.24
D(ECB_RATE)	0.04	2	0.98
D(INDUSTRIAL_PROD	5.89	2	0.05
All	15.84	8	0.04

Table 27 VEC Granger Causality Test of CSI 300 Informationtech (US)

Dependent variable: D(CSI_INFORMATION_TECH)

Excluded	Chi-sq	df	Prob.
D(IMPORTS_US)	4.40	2	0.11
D(FED_RATE)	1.82	2	0.40
D(INDUSTRIAL_PROD	1.06	2	0.59
D(INFLATION_US)	0.00	2	1.00
All	7.61	8	0.47

Dependent variable: D(IMPORTS_US)

Excluded	Chi-sq	df	Prob.
D(CSI_INFORMATION_	3.59	2	0.17
D(FED_RATE)	5.85	2	0.05
D(INDUSTRIAL_PROD	0.84	2	0.66
D(INFLATION_US)	2.57	2	0.28
All	19.88	8	0.01

Dependent variable: D(FED_RATE)

Excluded	Chi-sq	df	Prob.
D(CSI_INFORMATION_	4.47	2	0.11
D(IMPORTS_US)	3.69	2	0.16
D(INDUSTRIAL_PROD	9.25	2	0.01
D(INFLATION_US)	2.33	2	0.31
All	17.30	8	0.03

Dependent variable: D(INDUSTRIAL_PRODUCTION)

Excluded	Chi-sq	df	Prob.
D(CSI_INFORMATION_	0.70	2	0.71
D(IMPORTS_US)	0.92	2	0.63
D(FED_RATE)	0.84	2	0.66
D(INFLATION_US)	2.14	2	0.34
All	7.56	8	0.48

Dependent variable: D(INFLATION_US)

Excluded	Chi-sq	df	Prob.
D(CSI_INFORMATION_	6.70	2	0.04
D(IMPORTS_US)	0.13	2	0.94
D(FED_RATE)	16.98	2	0.00
D(INDUSTRIAL_PROD	2.73	2	0.26
All	27.67	8	0.00

Table 28 VEC Granger Causality of CSI 300 Informationtech (EU)

Dependent variable: D(CSI_INFORMATION_TECH)

Excluded	Chi-sq	df	Prob.
D(IMPORT_EU)	3.31	2	0.19
D(ECB_RATE)	2.56	2	0.28
D(INDUSTRIAL_PROD	6.19	2	0.05
D(INFLATION_EU)	1.69	2	0.43
All	12.72	8	0.12

Dependent variable: D(IMPORT_EU)

Excluded	Chi-sq	df	Prob.
D(CSI_INFORMATION_	6.76	2	0.03
D(ECB_RATE)	2.29	2	0.32
D(INDUSTRIAL_PROD	2.25	2	0.32
D(INFLATION_EU)	2.68	2	0.26
All	14.67	8	0.07

Dependent variable: D(ECB_RATE)

Excluded	Chi-sq	df	Prob.
D(CSI_INFORMATION_	1.17	2	0.56
D(IMPORT_EU)	6.82	2	0.03
D(INDUSTRIAL_PROD	4.77	2	0.09
D(INFLATION_EU)	14.90	2	0.00
All	29.46	8	0.00

Dependent variable: D(INDUSTRIAL_PRODUCTION)

Excluded	Chi-sq	df	Prob.
D(CSI_INFORMATION_	0.86	2	0.65
D(IMPORT_EU)	3.46	2	0.18
D(ECB_RATE)	6.54	2	0.04
D(INFLATION_EU)	0.52	2	0.77
All	19.29	8	0.01

Dependent variable: D(INFLATION_EU)

Excluded	Chi-sq	df	Prob.
D(CSI_INFORMATION_	3.05	2	0.22
D(IMPORT_EU)	2.64	2	0.27
D(ECB_RATE)	0.03	2	0.99
D(INDUSTRIAL_PROD	5.90	2	0.05
All	14.02	8	0.08

Table 29 VEC Granger Causality of CSI 300 Materials (US)

Dependent variable: D(CSI_MATERIALS)

Excluded	Chi-sq	df	Prob.
D(IMPORTS_US)	0.63	2	0.73
D(FED_RATE)	1.15	2	0.56
D(INDUSTRIAL_PROD	3.09	2	0.21
D(INFLATION_US)	1.96	2	0.38
All	8.09	8	0.43

Dependent variable: D(IMPORTS_US)

Excluded	Chi-sq	df	Prob.
D(CSI_MATERIALS)	2.34	2	0.31
D(FED_RATE)	5.80	2	0.06
D(INDUSTRIAL_PROD	0.58	2	0.75
D(INFLATION_US)	2.47	2	0.29
All	18.37	8	0.02

Dependent variable: D(FED_RATE)

Excluded	Chi-sq	df	Prob.
D(CSI_MATERIALS)	2.06	2	0.36
D(IMPORTS_US)	3.81	2	0.15
D(INDUSTRIAL_PROD	10.69	2	0.00
D(INFLATION_US)	1.68	2	0.43
All	16.53	8	0.04

Dependent variable: D(INDUSTRIAL_PRODUCTION)

Excluded	Chi-sq	df	Prob.
D(CSI_MATERIALS)	0.03	2	0.98
D(IMPORTS_US)	1.55	2	0.46
D(FED_RATE)	0.47	2	0.79
D(INFLATION_US)	2.68	2	0.26
All	6.04	8	0.64

Dependent variable: D(INFLATION_US)

Excluded	Chi-sq	df	Prob.
D(CSI_MATERIALS)	7.35	2	0.03
D(IMPORTS_US)	0.04	2	0.98
D(FED_RATE)	15.97	2	0.00
D(INDUSTRIAL_PROD	2.41	2	0.30
All	27.64	8	0.00

Table 30 VEC Granger Causality of CSI 300 Materials (EU)

Dependent variable: D(CSI_MATERIALS)

Excluded	Chi-sq	df	Prob.
D(IMPORT_EU)	1.17	2	0.56
D(ECB_RATE)	9.50	2	0.01
D(INDUSTRIAL_PROD	4.08	2	0.13
D(INFLATION_EU)	4.04	2	0.13
All	17.70	8	0.02

Dependent variable: D(IMPORT_EU)

Excluded	Chi-sq	df	Prob.
D(CSI_MATERIALS)	6.30	2	0.04
D(ECB_RATE)	3.51	2	0.17
D(INDUSTRIAL_PROD	0.21	2	0.90
D(INFLATION_EU)	2.26	2	0.32
All	12.77	8	0.12

Dependent variable: D(ECB_RATE)

Excluded	Chi-sq	df	Prob.
D(CSI_MATERIALS)	3.80	2	0.15
D(IMPORT_EU)	5.36	2	0.07
D(INDUSTRIAL_PROD	3.11	2	0.21
D(INFLATION_EU)	18.08	2	0.00
All	30.72	8	0.00

Dependent variable: D(INDUSTRIAL_PRODUCTION)

Excluded	Chi-sq	df	Prob.
D(CSI_MATERIALS)	0.57	2	0.75
D(IMPORT_EU)	2.87	2	0.24
D(ECB_RATE)	8.56	2	0.01
D(INFLATION_EU)	0.75	2	0.69
All	21.12	8	0.01

Dependent variable: D(INFLATION_EU)

Excluded	Chi-sq	df	Prob.
D(CSI_MATERIALS)	2.47	2	0.29
D(IMPORT_EU)	4.04	2	0.13
D(ECB_RATE)	0.16	2	0.92
D(INDUSTRIAL_PROD	3.84	2	0.15
All	14.96	8	0.06

Table 31 VEC Granger Causality of CSI 300 Industrial Production (US)

Dependent variable: D(CSI_INDUSTRIAL)

Excluded	Chi-sq	df	Prob.
D(IMPORTS_US)	4.76	2	0.09
D(FED_RATE)	3.24	2	0.20
D(INDUSTRIAL_PROD	2.82	2	0.24
D(INFLATION_US)	0.31	2	0.86
All	12.93	8	0.11

Dependent variable: D(IMPORTS_US)

Excluded	Chi-sq	df	Prob.
D(CSI_INDUSTRIAL)	2.98	2	0.22
D(FED_RATE)	5.13	2	0.08
D(INDUSTRIAL_PROD	0.77	2	0.68
D(INFLATION_US)	2.72	2	0.26
All	19.07	8	0.01

Dependent variable: D(FED_RATE)

Excluded	Chi-sq	df	Prob.
D(CSI_INDUSTRIAL)	1.20	2	0.55
D(IMPORTS_US)	3.70	2	0.16
D(INDUSTRIAL_PROD	7.23	2	0.03
D(INFLATION_US)	2.21	2	0.33
All	14.64	8	0.07

Dependent variable: D(INDUSTRIAL_PRODUCTION)

Excluded	Chi-sq	df	Prob.
D(CSI_INDUSTRIAL)	1.29	2	0.53
D(IMPORTS_US)	1.16	2	0.56
D(FED_RATE)	0.69	2	0.71
D(INFLATION_US)	1.95	2	0.38
All	7.74	8	0.46

Dependent variable: D(INFLATION_US)

Excluded	Chi-sq	df	Prob.
D(CSI_INDUSTRIAL)	4.54	2	0.10
D(IMPORTS_US)	0.29	2	0.86
D(FED_RATE)	15.13	2	0.00
D(INDUSTRIAL_PROD	2.78	2	0.25
All	25.33	8	0.00

Table 32 VEC Granger Causality of CSI 300 Industrial Production

Dependent variable: D(CSI_INDUSTRIAL)

Excluded	Chi-sq	df	Prob.
D(IMPORT_EU)	3.80	2	0.15
D(ECB_RATE)	6.77	2	0.03
D(INDUSTRIAL_PROD	2.87	2	0.24
D(INFLATION_EU)	0.66	2	0.72
All	12.94	8	0.11

Dependent variable: D(IMPORT_EU)

Excluded	Chi-sq	df	Prob.
D(CSI_INDUSTRIAL)	5.63	2	0.06
D(ECB_RATE)	4.30	2	0.12
D(INDUSTRIAL_PROD	0.86	2	0.65
D(INFLATION_EU)	2.09	2	0.35
All	13.64	8	0.09

Dependent variable: D(ECB_RATE)

Excluded	Chi-sq	df	Prob.
D(CSI_INDUSTRIAL)	6.35	2	0.04
D(IMPORT_EU)	6.67	2	0.04
D(INDUSTRIAL_PROD	4.38	2	0.11
D(INFLATION_EU)	19.27	2	0.00
All	35.50	8	0.00

Dependent variable: D(INDUSTRIAL_PRODUCTION)

Excluded	Chi-sq	df	Prob.
D(CSI_INDUSTRIAL)	3.05	2	0.22
D(IMPORT_EU)	3.59	2	0.17
D(ECB_RATE)	8.93	2	0.01
D(INFLATION_EU)	1.08	2	0.58
All	25.31	8	0.00

Dependent variable: D(INFLATION_EU)

Excluded	Chi-sq	df	Prob.
D(CSI_INDUSTRIAL)	3.32	2	0.19
D(IMPORT_EU)	3.40	2	0.18
D(ECB_RATE)	0.09	2	0.96
D(INDUSTRIAL_PROD	5.11	2	0.08
All	14.24	8	0.08

Table 33 Augmented Dickey-Fuller unit root test Shanghai Composite Index

Null Hypothesis: D(SHCOMP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.30	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 34 Augmented Dickey-Fuller unit root test CSI 300 Informationtech

Null Hypothesis: D(CSI_INFORMATION_TECH) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.58	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 35 Augmented Dickey-Fuller unit root test CSI 300 Materials

Null Hypothesis: D(CSI_MATERIALS) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.89	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 36 Augmented Dickey-Fuller unit root test CSI 300 Industrials

Null Hypothesis: D(CSI_INDUSTRIAL) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.08	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 37 Augmented Dickey-Fuller unit root test Inflation (US)

Null Hypothesis: D(INFLATION_US) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.15	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 38 Augmented Dickey-Fuller unit root test Inflation (EU)

Null Hypothesis: D(INFLATION_EU) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-8.65	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 39 Augmented Dickey-Fuller unit root test Import (US)

Null Hypothesis: D(IMPORTS_US) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.44	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 40 Augmented Dickey-Fuller unit root test Import (EU)

Null Hypothesis: D(IMPORT_EU) has a unit root
Exogenous: Constant
Lag Length: 11 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.67	0.08
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 41 Augmented Dickey-Fuller unit root test Federal Funds Rate (US)

Null Hypothesis: D(FED_RATE) has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.92	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 42 Augmented Dickey-Fuller unit root test European Central Bank Rate (EU)

Null Hypothesis: D(ECB_RATE) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.03	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 43 Augmented Dickey-Fuller unit root test Industrial Production (US)

Null Hypothesis: D(INDUSTRIAL_PRODUCTION) has a unit root
Exogenous: Constant
Lag Length: 12 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.58	0.01
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 44 Augmented Dickey-Fuller unit root test Industrial Production (EU)

Null Hypothesis: D(INDUSTRIAL_PRODUCTION) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.94	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 45 Phillips-Perron unit root test Shanghai Composite Index

Null Hypothesis: D(SHCOMP) has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-9.31	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 46 Phillips-Perron unit root test CSI 300 Informationtech

Null Hypothesis: D(CSI_INFORMATION_TECH) has a unit root
Exogenous: Constant
Bandwidth: 9 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-9.54	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 47 Phillips-Perron unit root test CSI 300 Materials

Null Hypothesis: D(CSI_MATERIALS) has a unit root
Exogenous: Constant
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-11.02	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 48 Phillips-Perron unit root test CSI 300 Industrials

Null Hypothesis: D(CSI_INDUSTRIAL) has a unit root
Exogenous: Constant
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-9.10	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 49 Phillips-Perron unit root test Inflation (US)

Null Hypothesis: D(INFLATION_US) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.15	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 50 Phillips-Perron unit root test Inflation (EU)

Null Hypothesis: D(INFLATION_EU) has a unit root
Exogenous: Constant
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.91	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 51 Phillips-Perron unit root test Import (US)

Null Hypothesis: D(IMPORTS_US) has a unit root
Exogenous: Constant
Bandwidth: 18 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-24.16	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 52 Phillips-Perron unit root test Import (EU)

Null Hypothesis: D(IMPORT_EU) has a unit root
Exogenous: Constant
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-14.05	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 53 Phillips-Perron unit root test Federal Funds Rate (US)

Null Hypothesis: D(FED_RATE) has a unit root
Exogenous: Constant
Bandwidth: 15 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.22	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 54 Phillips-Perron unit root test European Central Bank Rate (EU)

Null Hypothesis: D(ECB_RATE) has a unit root
Exogenous: Constant
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-4.12	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 55 Phillips-Perron unit root test Industrial Production (US)

Null Hypothesis: D(INDUSTRIAL_PRODUCTION) has a unit root
Exogenous: Constant
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-14.22	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.

Table 56 Phillips-Perron unit root test Industrial Production (EU)

Null Hypothesis: D(INDUSTRIAL_PRODUCTION) has a unit root
Exogenous: Constant
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-16.00	0.00
Test critical values:	1% level	-3.49	
	5% level	-2.89	
	10% level	-2.58	

*MacKinnon (1996) one-sided p-values.