THE INTERACTION OF REAL AND FINANCIAL MARKETS IN THE GLOBAL ECONOMY:

WHAT ROLE DOES CHINA PLAY?

by

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Abstract

This paper uses financial and industrial indicators in order to measure the interdependence of real and financial dynamics between several developed markets and China. We use realized volatility of stock prices and Industrial Production Growth to capture the dynamics in stock market and real economy respectively. Our main goal is to analyze whether there is a co-movement between China and developed markets in terms of industrial production and stock market volatility. We employ a Structural-VAR model with Sign Restrictions by constructing our indicators as monthly measures for 5-countries which are the US, the UK, Germany, Japan and China Our first result suggests that Chinese financial and production markets are disconnected, i.e. a shock to Chinese financial market has very little impact on its industrial production growth performance. Second, we find that China is more integrated to the world financial market via Hong Kong Stock Exchange channel, but relatively less through Shanghai Stock Exchange. Third, we observe a very close relationship between Japan, US, UK and Germany in terms of both industrial production and realized volatility. Also, with volatility-to-volatility sign restrictions imposed, we find that a volatility increase in one financial market increases other countries' realized volatility in the short-run. When we impose volatility-to-industrial production growth sign restrictions, we observe that an increase in volatility has a negative impact on other countries' industrial production growth in the short and middle-run. However, China has a different story: The movement in Chinese industrial production growth is mainly determined by its own domestic conditions, i.e. foreign markets has a relatively low impact on Chinese industrial production growth.

Keywords: Financial Markets, Industrial Production, Realized Volatility, China, Developed Markets.

Özet

Bu tez, finansal ve endüstriyel göstergeleri kullanarak Çin ve belirlenen bazı gelişmiş pazarların reel ve finansal dinamikleri arasındaki ilişkiyi incelemektedir. Finansal piyasalar ve reel ekonominin dinamiklerini temsil etmek için hisse fiyatlarının gerçekleşmiş finansal oynaklıkları ve sanayi üretimi büyümesi kullanılmaktadır. Bu çalışmanın ana amacı, bahsedilen bu değişkenleri kullanarak Çin ve gelişmiş piyasalar arasındaki dinamik ilişkiyi yakalamaktır. Belirlenen 5 ülkenin (Amerika Birleşik Devletleri, İngiltere, Almanya, Japonya ve Çin) aylık verileri üzerinden işaret kısıtlamaları yapılarak Yapısal Vektör Otoregresyon ekonometrik modeli kullanılmaktadır. Ampirik bulgularımız, ilk olarak, Çin Cumhuriyeti'nin finansal ve reel piyasalarının ayrışık olduğunu göstermektedir. Yani, Çin'in herhangi bir finansal sektörüne gelen oynaklığı arttırıcı bir şokun Çin'in sanayi üretimi performansı üzerinde çok az etkisi vardır. İkinci olarak, Çin finansal piyasalarının özellikle Hong Kong Borsası kanalıyla yabancı borsalar üzerinde etkisi olduğu tespit edilmiştir. Şangay Borsası'nın etkilerinin göreceli olarak daha domestik kaldığı gözlemlenmektedir. Üçüncü olarak, gelişmiş piyasalar (ABD, İngiltere, Almanya ve Japonya) arasında hem finansal sektörde hem de reel üretimde çok sıkı bir ilişki içerisinde oldukları gözlemlenmektedir. Bunlara ek olarak, uyguladığımız bazı işaret kısıtlarının sonucu olarak, finansal bir piyasada oynaklığı arttırıcı bir şokun diğer ülke finansal oynaklıkları üzerinde bulaşıcı ve pozitif etkisinin olduğu gözlemlenmektedir. Bunun aksine, finansal piyasalardaki bir şokun diğer ülke sanayi üretimi performansı üzerine daha geç etkisinin bulunduğu ve bu etkinin göreceli olarak daha az olduğunu tespit edilmektedir. Son olarak, Çin'in kendi sanayi üretim büyümesinin ülke içi dinamikler ile daha fazla etkileşimde olduğu ve yabancı piyasalar arasında en çok ABD'nin Çin'in endüstriyel performansına katkıda bulunduğunu gözlemlenmektedir.

Anahtar Kelimeler: Finansal Piyasalar, Sanayi Üretimi Büyümesi, Gerçekleşmiş Finansal Oynaklık, Çin, Gelişmiş Piyasalar.

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1. INTRODUCTION

Recent studies point out that many developed and emerging economies experience similar fluctuations in macroeconomic aggregates and there is a synchronization in fluctuations across countries and regions. Studies especially show that there is contemporaneous correlations in terms of output, consumption, investment and trade. The fact that there exist synchronized economic decisions in highly connected countries might redeem a global level shock very critical for the world economy. In particular, due to the possible strong linkages among economies, when a country faces a negative shock, there is a strong chance that it might be contagious such that other countries are also severely affected. Therefore, ignoring the underlying relation between real and financial markets misses an important part of the modern and integrated world economy. In that sense, the stock market is crucial as it channels funds to real economy. As a part of this function, the stock market is also a place where real economic productions are valued. Hence, the movements in stock prices are expected to reflect the changes in fundamental value of real economic activities. On the other hand, the production decision in one country is affected by the dynamics in other economies as well. In that regard, we know that global financial imbalances like increase in global financial volatility have important impacts on a country's production decision and financial dynamics.

Although the current literature emphasizes these common movements among countries, it usually disregards one of the most powerful economies due to several reasons such as unavailable or insufficient data: China. Since China has become the second largest economy in the world, we believe that the inclusion of Chinese data into our system is crucial in order to investigate the key role of Chinese financial system and production growth on other economies. In other words, we investigate the role of China in terms of how and through which channel it affects the financial markets and to what extent Chinese industrial production growth is affected by a volatility shock from other countries. In more detail, we hypothesize that there is no significant effect on Chinese industrial production growth from its own stock exchange markets due to the immature connection between real market and financial market. However, there is an indirect impact on Chinese industrial production performance via volatility channel such that the shock from Hong Kong and Shanghai Stock Exchange to foreign markets causes an increase in the volatility, and as a result, due to a fall in the demand the industrial production growth of China is negatively affected.

Our study is based on a set (#5) of countries: the US, the UK, Germany, Japan and China. We believe that such a country set strongly represents a dominant part of developed and emerging market economies that allows for the heterogeneity of experiences. More importantly, we add two stock exchange markets which are Shanghai Stock Exchange (SHCOMP) and Hong Kong Stock Exchange (HSI) for China. Since Hong Kong Stock Exchange market is observed to be more integrated and open market relative to Shanghai Stock Exchange, we take two stock markets into account for a better observation of Chinese financial market. In fact, Hong Kong has always been a very important stock market in China because unlike Shenzhen and Shanghai Stock Exchange markets, Hong Kong is the fully integrated stock exchange market into the global economy. For instance, **He, Liao and Wu (2014)** find that Hong Kong is more synchronized with the US more than with China in the short run whereas in the long run it is more correlated with China. Therefore, Hong Kong's exchange rate system, free capital mobility, bond - loan – and – equity financing make Hong Kong Stock Exchange (HSI) a thriving financial center. An important note here is that the correlation between Shanghai Stock Exchange and Hong Kong Stock Exchange is found to be 0.30 which is low enough to disregard suspicions about multicollinearity.

In order to characterize the heterogeneity of economic fluctuations in our sample, we employ a SVAR approach where the structure is partially identified with sign restrictions. Moreover, we look at generalized variance decompositions and impulse responses in order to better describe the connections in these countries. In terms of methodology, we know that under VAR model, ordering of variables matters significantly when there is orthogonalization of the reduced from residuals. In this case, a recursive identification scheme that depends on the ordering of the variables in the system is employed. Therefore, impulse responses under reduced form VAR model are not unique and it is mostly uncertain which impulse responses actually reflects the trends in a given system **(Lutkepohl, 2010).** Since Cholesky decomposition approach does not generally depend on economic intuitions and require a specific ordering in variables, results from impulse responses are unsatisfactory compared to a structurally designed system. Therefore, adoption of structural restrictions is required. Overall, we prefer using SVAR methodology which is also defined by **Lutkepohl (2010)** as "(…) a strategy to specify and estimate a reduced form model first and then focus on the structural parameters and the resulting structural impulse responses". In SVAR literature, **Sims (1981, 1986), Bernanke (1986), Shapiro and Watson (1988), Blanchard (1989)** first contributed to SVAR analysis with their studies. And recently, SVAR models have become a workhorse for empirical studies of macroeconomics and finance. First of all, we employ sign restrictions on our system. This type of modelling requires that each identified shock is associated with a unique sign pattern **(Lutkepohl, 2010).** We first make static restrictions such that we restrict the sign of our coefficients at time 0. Then we investigate a dynamic sign restriction case in which we impose restriction for longer horizons. The financial integration among countries and spillover effects resulting from the actions of the agents in the markets lead to a volatility increase in financially integrated countries. Moreover, volatility might create spillovers within the financial markets due to the behavioral biases, i.e., risk-averseness or institutional constraints. Due to such constraints agents might decrease their lending activities in an uncertain economic environment. As a result, this might cause a macroeconomic slowdown and might affect other markets' fundamentals negatively. Therefore, considering such a chain, we assign a positive sign to volatility-to-volatility relationship which implies that a volatility shock in a market causes a volatility increase in another market. Our second sign restriction is imposed on the channel from stock price volatility to industrial production growth. Again, we consider a static approach at t+0. Since volatility might have a delayed effect on production, we pose dynamic restrictions such that time is extended to t+1, t+2, t+3 and t+4.

The results from our analysis indicate that, first, Chinese production side and financial markets are almost disconnected. Secondly, we observe that financial markets of the foreign countries are heavily affected from Hong Kong Stock Exchange volatility, and relatively less from Shanghai Stock Exchange volatility. Third, the largest negative impact of a financial volatility shock on Chinese Industrial Production Growth comes from the US, others being low and mostly insignificant, yet the largest impact to Chinese industrial production growth merely comes from domestic conditions or domestic shocks. Apart from the Chinese story in our study, we also find that US, Japan, UK and Germany are actually more integrated and form a cluster such that interaction in terms of volatility and industrial production is very significant. Specifically, we too observe that there is a close connection among developed countries in terms of output and volatility. Similarly, **Kose, Otrok and Prasad (2008)** more recently exhibited that within industrialized economies there is a convergence of business cycle fluctuations. Therefore, our results are consistent with the literature in that regard. Also, we observe that a financial volatility shock in a country is generally reflected on industrial production growth at t+3 whereas the effect of a financial volatility shock in a country on other countries' financial volatility is quickly observed at t+1 and t+2, and the impact seems to stay for a longer period. More importantly, Hong Kong Stock Exchange seems to have the highest power of negatively affecting other financial markets.

The remainder of the paper is structured as follows. Section 2 introduces the literature review. Section 3 is based on the data sources. Section 4 explains our econometric model as our methodology. In section 5, we give the interpretations of our coefficients and success of our restrictions. Section 6 discusses the relative importance of Chinese real and financial economy on the dynamics of other selected countries' industrial production and realized volatility. We conclude by discussing our results and possible extensions.

2. LITERATURE REVIEW

Recently, the phenomenon about the de-coupling or divergence between Emerging Market Economies (EMEs) and Developed Market Economies captured the attentions of many scholars. Many recent studies show that there is business cycle similarities and international co-movement among countries, i.e. contemporaneous correlations in terms of output, consumption, investment and trade. Recently, the phenomenon about the de-coupling or divergence between Emerging Market Economies (EMEs) and Developed Market Economies captured the attentions of many scholars. For instance, **Backus et al. (1993)** reveal that there is a synchronization among developed economies. Similarly, **Baxter (1995)** finds that there is a definite tendency for business cycles in major industrialized economies as well. In a much recent study, **Kose, Otrok and Prasad (2008)** exhibit that within industrialized economies and emerging markets there is a convergence of fluctuations and they observe that there is a decoupling trend between these two groups of countries. **Benczur and Ratfai (2009)** examine the characteristics of 62 countries in order to uncover the sources of fluctuations in industrialized and emerging market economies. In terms of revealing the relationship between developed and emerging market economies, several studies investigate the connection between industrial production and stock market volatility as a proxy for real production and finance. For instance, an earlier study done by **Errunza and Hogan (1998)** find that European stock return volatility could be explained to some extent by industrial production for several European countries. Furthermore, **Goswami and Jung (1997)** reveals a similar conclusion such that stock market movements and GDP, Industrial Production, oil prices and interest rates have a positive relationship in Korean market. Lastly, **Wongbangpo and Sharma (2002)** observe that in ASEAN-5 countries (Thailand, Indonesia, Malaysia, Singapore and Philippines) stock markets are dynamically interact with their macroeconomic aggregates both in the long and in the short run.

Moreover, in the literature, it is assumed that when the markets are financially integrated, an unexpected event in one market influences not only return but also variance in the other markets **(Joshi and Pandya, 2012). Strohsal and Weber** (2015) state that if higher volatility in one market leads to an increase in volatility of another market, then the characteristics of volatility is related to the information hypothesis used by **Epps and Epps (1976), Ross (1989) and Fleming (1998)** as well. Information hypothesis suggests that high volatility in the target market associated with high spillover power to other financial markets. In that regard**, Bala and Premaratne (2004)** argue that volatility in financial markets impose significant impacts on behaviors of the investors and look for a volatility co-movement among several financial markets. They especially find significant evidence for volatility co-movement among Hong Kong - US and Japan - the UK. Very recently, a real life example Brexit case on 24th of June in 2016 was observed to create ramifications on stock market volatilities of many countries. German Stock Index (DAX), Tokyo Stock Index (Nikkei 225), New York Stock Exchange (NYSE), Hong Kong Stock Exchange (HSI) and Shanghai Stock Exchange (SHCOMP) stock price volatilities significantly increased due to spillover effects. Additionally, **Sheicher (2001)** identify regional and global shocks in terms of financial integration and they find that innovations to volatility have a primarily regional character. **IMF Report (2015)** states that financial development and stability stimulates a country's economic growth by promoting information sharing, resource allocation and management of risk. In addition, in the report it is stated that stock market volatility is successful at capturing the trends in economic growth at a 6-month and one-year period. For instance, **Fornari and Mele (2009)** find that stock market volatility is able to explain the future real economic growth up to 55% at one and two year horizons. They state that during "Great Moderation" period, predictive power of stock market volatility increased significantly. Also, **Papadopoulos et al (2011)** make an analysis investigating the relationship among several macroeconomic and financial indicators in 12 European countries and they find that between stock market prices and industrial production exhibits a negative relationship.

3. DATA

Our analysis basically processes two variables for each country selected. First, we use seasonally adjusted industrial production indices at monthly frequency. They are all seasonally adjusted series with the same base year (2010). We use monthly data because it allows us to capture the links between shocks in the markets much faster. For stationarity purpose, we convert Industrial Production Index data to Industrial Production Growth multiplied by 100. Industrial Production data is obtained from OECD database. Industrial production growth data is used as a proxy for economic activity. Therefore, results obtained from industrial production growth help us understand what happens in the real side of the economies. Second, we construct monthly average realized volatility for each country by using stock exchange daily last prices. We first get stock exchange last prices from Bloomberg Database for each stock market. Since they are daily data, we transform them into monthly realized volatility data by simply calculating monthly sample variance. Then, we take the log of realized volatility for each market. **Andersen, Bollerslev, and Diebold (2010)** state that if the realized volatility approach is categorized for price observations within an interval [t-h,t], then this approach is said to be asymptotically unbiased and approximately serially uncorrelated under quite general conditions.

Observation date of both variables starts from 1999:02 to 2014:5 and they are obtained on a monthly basis. The choice of sample period is due to the fact that Chinese Industrial Production Index data starts from 1999. Also, we have 185 observations for all variables in the system, covering 15 years. Moreover, an important note is that for China, Shanghai Stock Exchange Market and Hong-Kong Stock Exchange Market are both included into our system in order to analyze the degree of Chinese financial integration into world financial system.

4. METHODOLOGY

4.1. Vector-Autoregressive Model (VAR(p))

As Sims (1980) pioneered, VAR models have acquired a coherent and credible place in the toolkit of macroeconomists for data description, forecasting, and structural inference and conducting policy experiments. VAR models are generally used in order to capture empirical evidence about rich dynamics of multiple time series. In our study, we use a multivariate VAR model by using Industrial Production Growth and Realized Volatility data of 5 countries selected. For p lags and K number of variables, VAR (p) model is as follows:

$$\mathbf{y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t} \quad \textbf{for } \mathbf{t=0,1,2 \ldots}$$

where $\mathbf{y_t = (y_{1t}, \ldots, y_{Kt})'}$ is a **(K x 1)** random vector. The $\mathbf{A_i}$ matrices are the coefficient matrices with **(K x K)** dimension and intercepts are a **(K x 1)** matrix such that $\mathbf{v = (v_1,\ldots,v_K)}$. Also, residuals are white noise, i.e.;

i. $\mathbf{E(u_t) = 0}$,

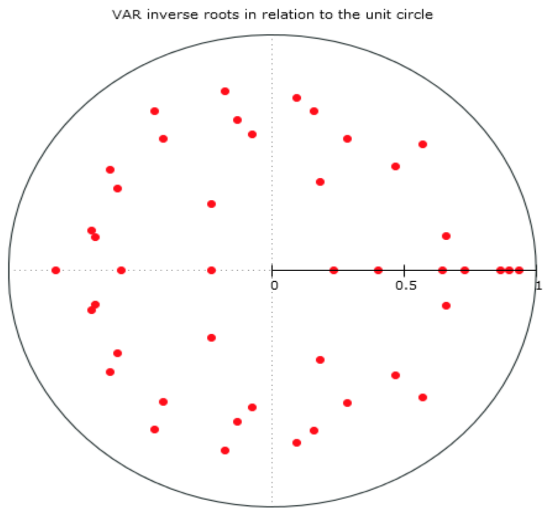
ii. $\mathbf{E(u_t u_t') = \sum_u}$,

iii. $\mathbf{E(u_t u_s') = 0}$ **for** $\mathbf{s \neq t}$.

For our case, lag number is determined to be 4. We believe that a shock to volatility is captured by the industrial production with a delay. Therefore, embracing a 4-lag VAR model provides coherent information so as to form a relationship between financial volatilities and economic activities among selected countries. One of the most important characteristics of a VAR model is stability generating stationary time series such that means, variances and co-variances are time invariant. Stability condition is satisfied if the following statement holds for all roots:

$$\mathbf{det\,(I_K - A_1 z - \ldots - A_P z^P) \neq 0 \text{ for } |z| \leq 1.}$$

In our study, we find all our variables stationary. Tests are performed and the unit circle below shows that each root is in the circle suggesting that we have a stationary system so that we can continue with stationary VAR model. Since we have more than one lag, we use ADF test in order to check for stationarity. All our variables are stationary when checked with tau-statistics table (Table K, see Appendix A). We test both the industrial production growth series and realized volatility series using Augmented Dickey Fuller test (ADF). We find that there is no evidence for unit root in any series. On the contrary, we find overwhelming evidence against the unit root in each series, suggesting that our variables are all I(0). Below, the unit circle is also shown such that the inverse roots lie with the unit circle suggesting stationarity.



Hence, we can conclude that our system is stationary. In the following section, we focus on Structural Vector-auto-regressions and Sign Restrictions for our study.

4.2 Structural VAR: Sign Restrictions

Under VAR model, impulse responses are crucial in terms of analyzing the relations between the variables. However, there are some problems in their interpretations due to several obstacles. First of all, the impulse responses are not unique and it is mostly uncertain which impulse responses actually reflects the trends in a given system (Lutkepohl, 2010). Secondly, orthogonalization by Cholesky decomposition means that we impose a particular causal chain on variables rather than learning about causal relationships from the data (**Casson, 2013**). So, the mathematical Cholesky ordering does not make economic sense unless there is a plausible theoretical explanation for the recursive ordering. Therefore, structural interpretations based on economic theory or institutional knowledge should be motivated for a better identification of relevant variables and impulse responses. Only after decomposing forecast errors into structural shocks that are mutually uncorrelated and have an economic interpretation can we assess the causal effects of these shocks on the model variables (**Casson,2013**). In the earlier studies, many VAR papers overlooked these problems and presented economically meaningless results of VAR impulse responses and forecast error variance decompositions. Hence, we prefer using structural restrictions imposed on a VAR model which is an approach pioneered **by Faust (1998), Canova and De Nicolo (2002) and Uhlig (2005)** in the context of VAR models of monetary policy. For instance, Uhlig (2005) showed that sign-identified models may produce substantially different results from conventional structural VAR models. Sign-identified VAR models have become increasingly popular in other areas as well and are now part of the mainstream of empirical macroeconomics (**Casson,2013**).

ASSUMPTION 1. A realized volatility impulse vector is an impulse vector such that the impulse responses to realized volatility shock has negative impact on industrial production growth and the impulse responses are negative, for all countries N = 1,…,5 and at t+0,t+1,t+2,and t+3.

Table 1: Volatility-to-Industrial Production Growth Restrictions

$$
\begin{pmatrix} u_t^1 \\ u_t^2 \\ u_t^3 \\ u_t^4 \\ u_t^5 \\ u_t^6 \\ u_t^7 \\ u_t^8 \\ u_t^9 \\ u_t^{10} \\ u_t^{11} \end{pmatrix}
=
\begin{bmatrix}
X & X & X & X & X & - & - & - & - & - & - \\
X & X & X & X & X & - & N & - & - & - & N \\
X & X & X & X & X & - & - & - & - & - & - \\
X & X & X & X & X & - & - & - & - & - & - \\
X & X & X & X & X & - & - & - & - & - & - \\
X & X & X & X & X & X & X & X & X & X & X \\
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X & X & X & X & X & X & X & X & X & X & X \\
X & X & X & X & X & X & X & X & X & X & X
\end{bmatrix}
*
\begin{pmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \\ \varepsilon_t^3 \\ \varepsilon_t^4 \\ \varepsilon_t^5 \\ \varepsilon_t^6 \\ \varepsilon_t^7 \\ \varepsilon_t^8 \\ \varepsilon_t^9 \\ \varepsilon_t^{10} \\ \varepsilon_t^{11} \end{pmatrix}
$$

where – above and + below denote the postulated sign of the impact response and × denotes no restriction. Table 1 shows the negative sign restriction of the effects of realized volatility to industrial production growth. An important note here is that we assume a non-negative impact from Chinese financial markets to Chinese industrial production growth. The colored (N) in Table 1 suggests this non-negative assumption. The basic reason behind this assumption is that due to the disconnection between financial and real markets of China we expect that if a volatility increase happen in Chinese markets, then this volatility increase is not realized as a “negative” ramification on the production side since they are already separated markets. Therefore, finding non-negative successful sign restrictions for China will tell us that a shock happening in financial markets is not negatively reflected on production growth of China.

Table 2 below shows the positive sign restriction of the effects of realized volatility to volatility. The Assumption 2 is valid for all countries.

ASSUMPTION 2. A realized volatility impulse vector is an impulse vector such that the impulse responses to realized volatility shock has positive impact on volatility and the impulse responses are positive, for all countries N = 1,…,5 and at t+0,t+1,t+2,and t+3.

TABLE 2: Volatility-to-Volatility Restrictions

$$\begin{pmatrix} u_t^1 \\ u_t^2 \\ u_t^3 \\ u_t^4 \\ u_t^5 \\ u_t^6 \\ u_t^7 \\ u_t^8 \\ u_t^9 \\ u_t^{10} \\ u_t^{11} \end{pmatrix} = \begin{bmatrix} X & X & X & X & X & X & X & X & X & X & X \\ X & X & X & X & X & X & X & X & X & X & X \\ X & X & X & X & X & X & X & X & X & X & X \\ X & X & X & X & X & X & X & X & X & X & X \\ X & X & X & X & X & X & X & X & X & X & X \\ X & X & X & X & X & + & + & + & + & + & + \\ X & X & X & X & X & + & + & + & + & + & + \\ X & X & X & X & X & + & + & + & + & + & + \\ X & X & X & X & X & + & + & + & + & + & + \\ X & X & X & X & X & + & + & + & + & + & + \\ X & X & X & X & X & + & + & + & + & + & + \end{bmatrix} * \begin{pmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \\ \varepsilon_t^3 \\ \varepsilon_t^4 \\ \varepsilon_t^5 \\ \varepsilon_t^6 \\ \varepsilon_t^7 \\ \varepsilon_t^8 \\ \varepsilon_t^9 \\ \varepsilon_t^{10} \\ \varepsilon_t^{11} \end{pmatrix}$$

We impose negative and positive restrictions separately. Our model is partially identified such that response to a volatility increase by industrial production growth and volatility is identified. We first make identifying restriction at time zero which is a static analysis. Then, we look at further time delays for volatility and industrial production growth relationship. This is merely due to the fact any shock in financial market might have a delayed effect on industrial production growth. Therefore, by putting restrictions to further months we sharpen our inferences considerably. Similar study is done also by Inoue and Kilian (2013). They find a negative effect of a sudden change monetary policy tightening to real GDP in month 6 such that in a foreseeable future they are able to show a decline in real activity.

4.3. Characteristics of a Structural-VAR Model

Sign identification is based on qualitative restriction involving the sign of some shocks on some variables (Gambetti & D'agostino,2013). So we have sets of consistent impulse response functions. In this section, we characterize the priors that are implicit in the VAR models with sign restrictions. First of all, forecast errors, u_t from reduced form models are constructed as linear functions of the structural innovations, e_t such that:

$$\mathbf{u_t = B\varepsilon_t \quad \varepsilon_t \sim N\,(0,I_K).}$$

The i^{th} column of B corresponds to the i^{th} impulse vector. That is, the i^{th} column of matrix B is the representation of an innovation in the i^{th} structural variable as a one-step ahead prediction error (Uhlig, 2005). Put differently, the i^{th} column of B describes the immediate impact on all variables of an innovation in the i^{th} structural variable. Then, given that $\mathbf{u_t = B\varepsilon_t}$, we can write:

$$\mathbf{\textstyle\sum_u = B\sum_\varepsilon B'}$$

$$\mathbf{\textstyle\sum_u = BB'}$$

where we further impose K restrictions assuming that $\boldsymbol{\varepsilon_t}$'s are standardized, hence $\mathbf{\sum_\varepsilon = I_K}$. Then, let P denote the Cholesky decomposition of $\sum_\mathbf{u}$ such that $\mathbf{\sum_u = PP'}$. Notice that $\mathbf{B = PD}$ also satisfies $\mathbf{\sum_u = PDD'P' = PIP' = PP'}$ for any orthogonal matrix (i.e. $\mathbf{DD' = I}$). Unlike P, PD is in general non-recursive. We can examine a wide range of possible solutions B by repeatedly drawing at random from the set of α of orthogonal matrices **D**. In order to obtain the desired system with sign restrictions, we first make a **QR** decomposition such that $\mathbf{L}_{\mathbf{K}\times\mathbf{K}}$ **= QR** and **QQ' = I**. Then, for **D = Q'** we compute impulse responses using the orthogonalization **B = PD.** If the impulse response functions satisfy the identifying restrictions, we retain **D**. We do these two steps for 10.000 times so that we get more information about restrictions.

5. RESULTS

5.1. Results of VAR coefficients

Since we are making assumptions for sign restrictions in the following sections, it is important to check the t-significances from VAR results of the coefficients. We divide the significance test results into 3 subsections. First, we investigate the industrial production growth coefficients by looking at cross-relations with other countries' industrial production growth variables. In the second subsection, we consider coefficients resulting from the lags of realized volatility to industrial production growth of each country. In the last subsection, we consider coefficients resulting from the lags of realized volatility to volatility of each country.

5.1.1. Industrial Production Coefficients

First of all, we observe that the link between realized volatility and industrial production growth is rather low compared to the link between industrial production growths of each country. That is, there exists a cluster such that real market indicators affect each other considerably but *relatively* less affected from the realized volatility. We mostly find a positive relationship among all countries with several exceptions. First, we see a positive drive from the US production growth to the UK, Germany and Japan. That is, the increase in the production growth of the US gives rise to the production growth of UK, Japan, and Germany with coefficients being (0.31), (1.02) and (0.59) with t-statistics [2.914], [3.262] and [3.467] respectively in the short run. Similarly, an increase in the production growth of the UK pushes the production growth of Japan, the US and Germany up significantly with coefficients being (0.57), (0.13) and (0.37) with t-statistics [2.803], [2.149] and [2.621] respectively in the short run. The same pattern is also observed for Germany such that it gives rise to production growth of the UK with the coefficient being (0.077) with t-statistics [1.688], Japan with the coefficient being (0.26) with t-statistics [2.133] and US with the coefficient being (0.058) with t-statistics [1.707]. Likewise, Japan provides a similar information in terms of a positive effect on production growths of the US, UK and Germany with coefficients being (0.08), (0.07) and (0.21) with t-statistics [1.848], [3.249], and [3.391] respectively. This co-movement in terms of industrial production is also found by Kose et al(2003) suggesting that among developed markets there exists a synchronization in terms of ouput, investment and consumption. Lastly, the case of China slightly differ from other results such that only US production growth seems to have a significant impact on Chinese production growth, the coefficient being (-0.73) with t-statistics [-2.073]. Interestingly, there is an asymmetric relationship such that the effect from Chinese production growth to that of US is positive by (0.04) with t-statistics [1.892]. In addition, we observe that Chinese production is mainly affected from itself, but very least from other production growths.

5.1.2. From Volatility-to-Industrial Production Growth Coefficients

As we consider the sign restrictions, it is crucial to check for the significance of the coefficients from volatility to industrial production growths. The first important result we get from our analysis is that realized volatility in Japan affects the industrial production growths negatively and significantly in the short run -though we observe *relatively* low and insignificant effect to UK production growth. For instance, industrial production growth of China is affected negatively from the stock market volatility in Japan, where the coefficients is (-0.42) with t-statistics [-1.759]. Also, industrial production growth of the US is affected negatively from stock market volatility in Japan by (-0.11) with t-statistics [-2.043] as well as Germany being affected by (-0.27) with t-statistics [-1.960]. More interestingly, in our system Japan seems to be the most vulnerable and connected industrial production market to any changes in both industrial production performances and stock market volatilities of other countries. Its production growth is negatively and highly affected from an increase in volatility of the UK, the US and Hong Kong Stock Exchange market, the coefficients being (-0.82), (-0.62) and (-0.48) with t-statistics [-2.722], [-2.008] and [-1.971] respectively. Apart from the vulnerability of Japanese production to volatility shocks from outside and that production growth performances being disturbed from Japanese volatility, our results mostly provide insignificant effects of volatility on production growth. In our results, successful number of sign restriction for Assumption 1 holds for lower numbers in 10.000 trials compared to Assumption 2.

5.1.3. From Volatility-to-Volatility Coefficients

In this part, we control for the coefficients of volatility and find several significant results. First of all, the most dominant result is that Hong Kong Stock Exchange volatility impact on other stock market volatilities is considerably significant and positive. It increases the volatilities of the UK, Shanghai, Japan and the US positively, coefficients being (0.14), (0.23), (0.25) and (0.187) with t-statistics [1.7], [1.937], [2.31] and [1.92].

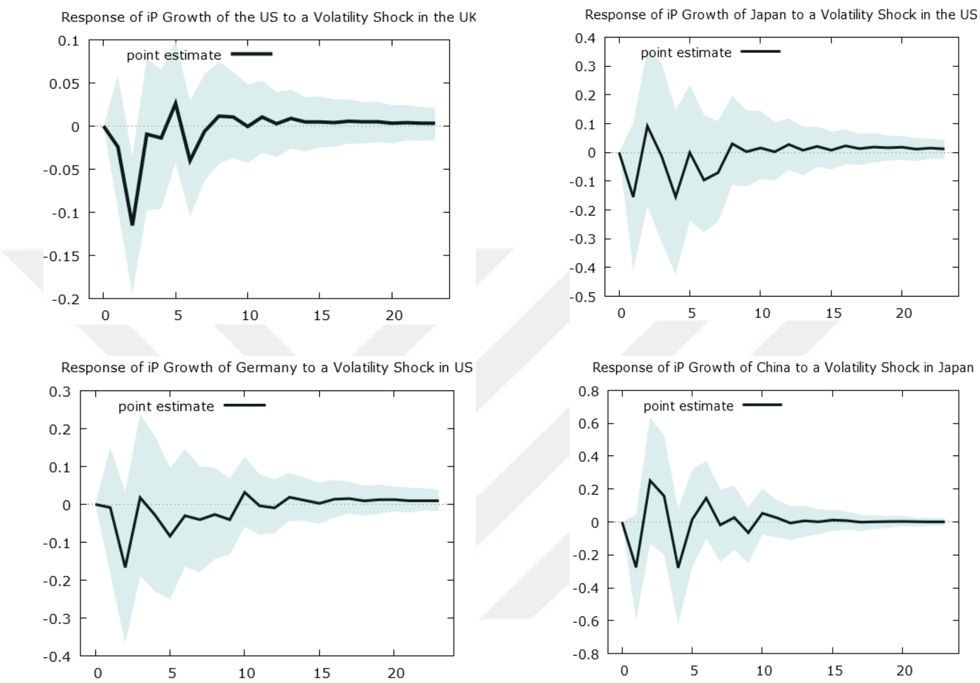
Also, for most of our variables we observe that lagged volatility effects are highly significant and positive, i.e. each market's volatility is significantly affected from their own volatility spillover higher than cross-volatility spillover. For instance, for the UK, the impact from its own lagged variable is significant such that the coefficient is (0.24) with t-statistics [2.001]. Another example is Japan whose lagged volatility variable has significant and positive impact on the volatility of itself, with a coefficient being (0.22) with t-statistics [2.545]. This phenomenon is also mentioned in several papers.

Worthington and Higgs (2004) find that own stock market volatility spillovers are generally higher than cross-volatility spillovers for all markets. Moreover, Kose et al (2008) states that "in Asia, country factor plays the dominant role in explaining the volatilities of growth in output (…). [And] country factors explain about 70% of output variation (…)".

5.2. Results of Volatility-to-Industrial Production Growth Restrictions

As we discussed the significant test results, it is crucial to have our sign restrictions be in line with them. Under the first sign restriction case, i.e. negative response of industrial production growth to volatility shocks, we observe a similar pattern in all markets. First of all, we observe a considerable increase in the number of satisfied sign restrictions in the 2nd and 3rd month which is denoted as horizon (t+2) and (t+3) respectively showing the effect of volatility shock to industrial production (see Appendix A, Table R1). The success of trials is at highest **13%**, which belongs to the US effect. That is, a financial volatility shock in the US has the highest negative effect on industrial production growth in all countries. Moreover, **US** is followed by a volatility shock in **Hong Kong** and **Germany** which has the 2nd and 3rd highest negative effects respectively on industrial production growths by **11,8%** and **11,1%** (see Appendix A). Hence, our first restriction assumption holds for these countries considerably whereas under **Japan**, **the UK** and **Shanghai** cases we find less significant number of sign restrictions. In all markets, we observe a delayed effect of volatility on industrial production growth. Therefore, the choice of lag of 4 makes sense in terms of analyzing the relationship between a financial environment and production side. Moreover, via the results from sign restrictions we observe a delayed effect of volatility shock on industrial production growths of countries. As seen in the below several impulse response graphs, we observe the effect on 2nd and 3rd months are dominant in terms of causing a fall in the industrial production growth. In order to have a better understanding, we also check the Generalized Impulse Responses. And we still observe the same pattern in generalized impulse responses as well. (See Appendix A)

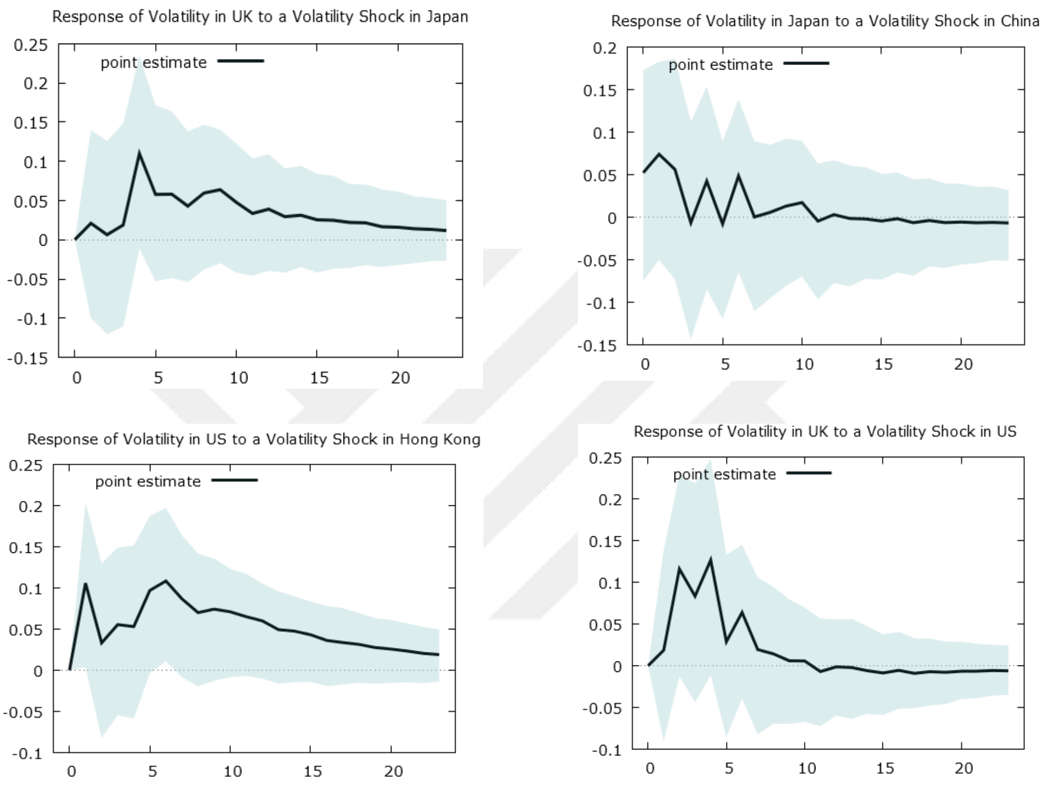
Figure 1: Responses of Several IP Growths to Volatility Shocks



5.3. Results of Volatility-to-Volatility Restrictions

On the other hand, we find that our second assumption holds more significantly in terms of successful number of satisfied sign restrictions, generalized variance decompositions and impulse responses. Overall, we observe that at t+2, there is a significant jump in the successful number of positive sign restrictions. In other words, when there is a positive shock in volatility in one market, positive effect to other markets become evident at t+2 except for a shock coming from the US. In the US case, we observe a different pattern such that at t+1 the financial shock in the US is quickly spread to the other markets and number of success of our restrictions increases by **62.5%** from t+0 to t+1. Also, we see that our restrictions hold by **15%** on average at t+2 for all markets. Besides, the most interesting outcome emerges with the Hong Kong effect. We find that an increase in the financial volatility of **Hong Kong Stock Exchange** increases volatility of other financial markets overwhelmingly at horizons t+0, t+1 and t+2 (see Appendix A). The number of success of trials holds for **20.4%** at t+1 and **24.8%** at t+2, highest overall.

Figure 2: Responses of Several Volatilities to Volatility Shocks

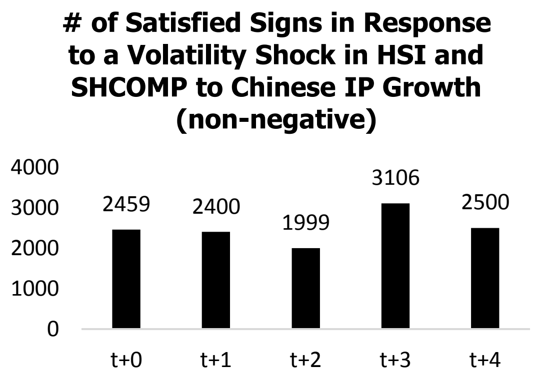


6. AN INVESTIGATION ON THE IMPORTANCE OF CHINESE ECONOMY

6.1. Chinese Financial Shock Effect on Chinese IP Growth

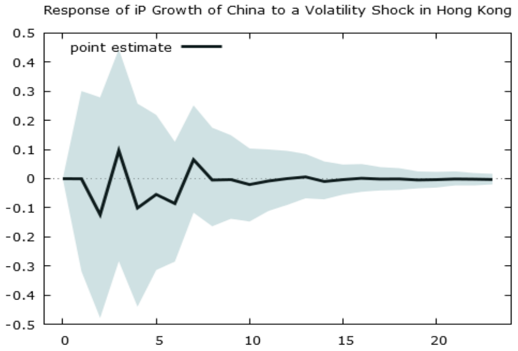
Since we investigate the role of China in terms of how and through which channel it affects the financial markets and to what extent Chinese industrial production growth is affected by a shock from other countries, in this section we especially focus on how Chinese industrial production growth and financial volatility interaction. That is, we question the degree of the synchronization between Chinese financial sector and real sector. This investigation is mainly due to the fact that despite the fast growth of the stock market in China, an ineffective and limited connection exists between the growing financial market and the real sector**. Allen, Qian and Qian (2005)** state that the financial markets in China have not been effective in allocating resources in the economy and they are highly speculative and driven by insider trading. Therefore, we hypothesize that there is no significant effect on Chinese industrial production growth by its own stock exchange markets. However, we also hypothesize that there is an indirect impact on Chinese industrial production performance via volatility channel such that the shock from either Hong Kong or Shanghai Stock Exchange to foreign markets causes an increase in the volatility and therefore a fall in the demand is realized, and hence the industrial production growth of China is negatively affected. In 12 June 2015 the Chinese stock market turbulence occurred and caused A-shares which are of the Renminbi currency that are purchased and traded in Shanghai Stock Exchange and Shenzhen stock exchanges dropped by one third and Shanghai Stock Exchange market had fallen by 30%. However, both indirect and direct impact from such turbulence on real production were observed to be quite limited. Hence, our intuition behind such hypotheses lean on real observations in the world. In order to do investigate, we check for sign restrictions, the generalized variance decompositions and impulse responses. For sign restrictions, we especially impose non-negative impact from Chinese financial markets to Chinese production growth as explained under Assumption 1. First of all, we find that the impact on industrial production growth of a specific shock to both Hong Kong and Shanghai Stock Exchange is very weak. The non-negativity restriction is observed to be valid because the successful number of non-negative sign restrictions hold for on average about 25% of 10.000 trials as shown below.

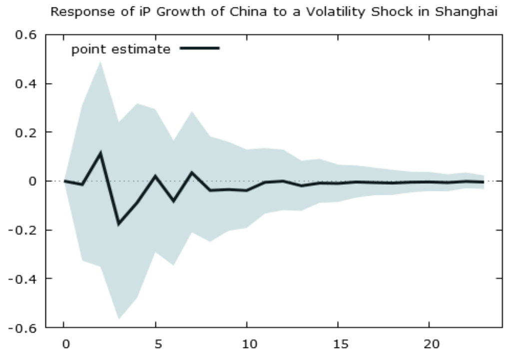
Figure 3: Number of Successful Chinese Volatility-to-Chinese IP Growth Sign Restrictions



Numerically, the generalized variance decomposition tells us that a shock in Shanghai Stock Exchange affects the production growth by only 0.19% and Hong Kong Stock Exchange affects by 0.50% (See Table V1,Appendix A). The biggest impact to Chinese Industrial Production Growth comes from its own industrial production growth. That is, Chinese industrial production growth variance is responsible for the variation by about 95% (See Table V1, Appendix A). Moreover, this result changes very slightly under t+3 and t+4 variance decompositions (See Table V2 and V3, Appendix A). And the closest percentage to 95% is followed by the US volatility with 2.2%. As a result, we can conclude that Chinese production growth is mainly affected from itself followed by 2.2% US Volatility. As shown below, impulse responses reflect almost no reaction at t+0 and t+1, but then there occurs to be movement which die out after t+4. Generalized impulse responses reflect a similar pattern as well (See TABLE P1, Appendix A).

Figure 4: Responses of Chinese IP Growth to Volatility Shocks in Shanghai and Hong Kong

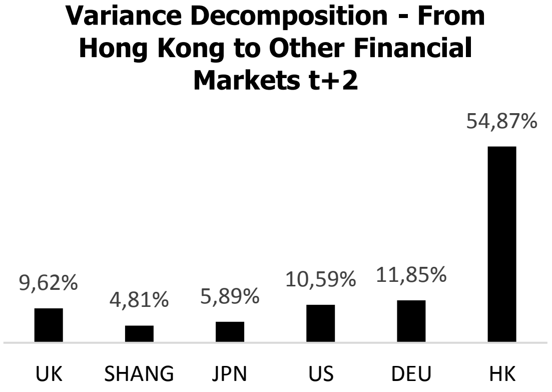


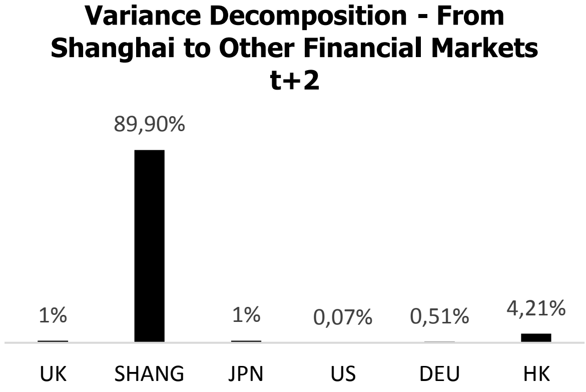


6.2. Chinese Financial Shock Effect on Volatility of Other Markets

There are two main stock exchanges in China: the Shanghai Stock Exchange and the Shenzhen Stock Exchange. As stated by Elliott and Yan(2013), another major stock exchange in China is Hong Kong Stock Exchange which traditionally focuses on the equities of locally based firms, but has expanded to trade a considerable volume of H-shares (shares of companies located in Chinese territories traded on Hong Kong SE). Having said that China has three important stock exchange markets, the question emerges: “how influential is Chinese financial system on foreign markets?” As we see the generalized variance decompositions below for t+2 (and almost the same for t+3), Hong Kong Stock Exchange market is easily observed to be the most influential market on the foreign markets more than Shanghai Stock Exchange market. This generalized variance decomposition tells us that at t+2 by how much Hong Kong Stock Exchange market is responsible for the variation in other markets. For example, at t+2, Hong Kong is responsible for a variation in the US by 10.59%, in Germany by 11.85%, in the UK by 9.62%, in Japan by 5.89% and lastly in Shanghai by 4.81% whereas Shanghai is responsible for considerably lower variations in foreign markets such as 0.07% of the US volatility, 0.51% of the Germany volatility, 1% of the UK volatility,1% of the Japan volatility, and 4.21% of the Hong Kong volatility.

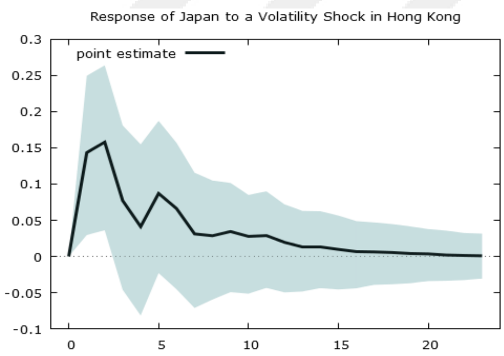
Figure 5: Generalized Variance Decomposition at t+2

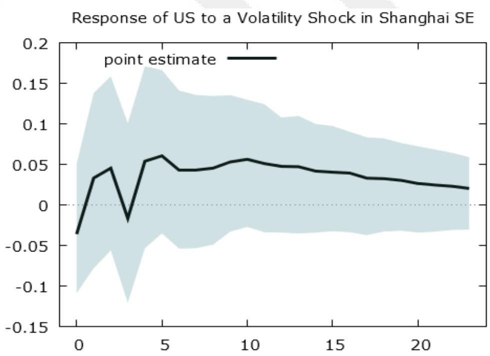




As examples, the impulse responses below also show the impulse responses of Japan to a volatility shock in Hong Kong SE market and the US to Shanghai SE market, suggesting the shock is accompanied by an increase in the volatility of the both Japan and the US financial markets. And interestingly we observe that shocks continue for a prolonged time, i.e. there is still some impact left after t+4.

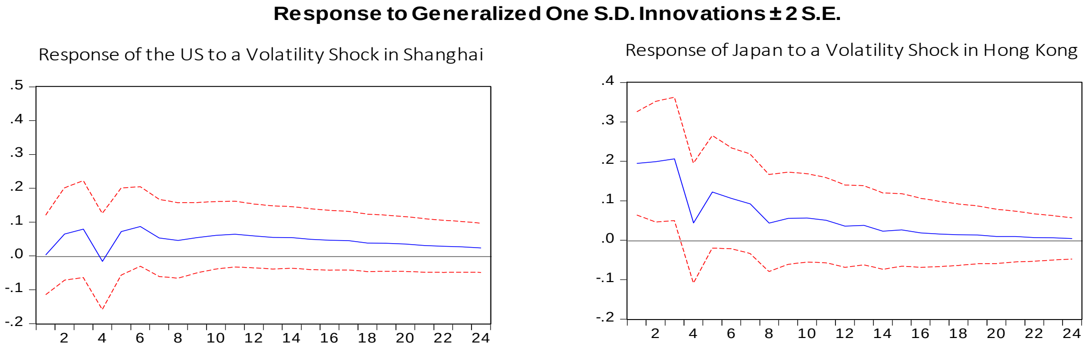
Figure 6: Responses of Volatility in Japan and the US to Chinese Financial Shocks





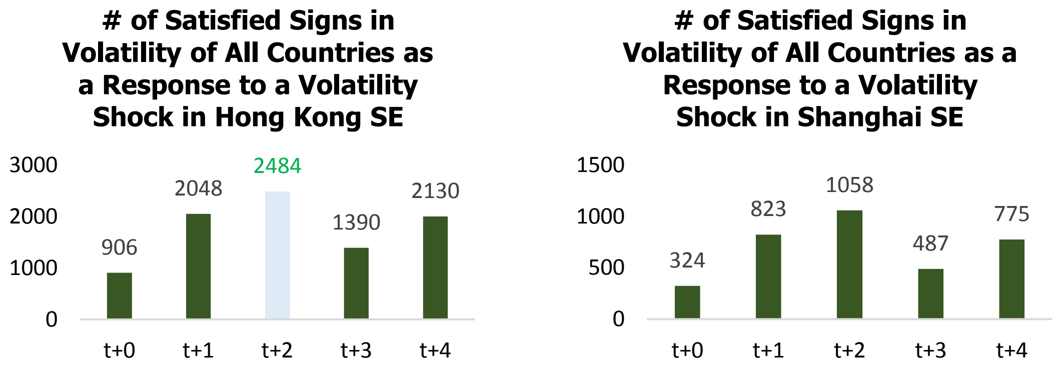
This argument is also observed under sign restrictions as well. Their generalized impulse responses are also shown as below.

Figure 7: Generalized Responses of Volatility in Japan and the US to Chinese Financial Shocks



As we see from the bar chart below displaying the number of satisfied sign restrictions, after the impact of a volatility shock in Hong Kong SE reached to the peak level, the impact slightly dies out but still is observed to be persistent. Moreover, among all number of satisfied signs, Hong Kong has the highest success followed by the US, i.e. almost 25% of sign restrictions hold for Hong Kong as seen below whereas in other markets it is stuck around 15%. Shanghai is relatively lower than Hong Kong's sign restriction success.

Figure 8: Number of Successful Chinese Volatility-to-Other Countries' Volatility Sign Restrictions



Overall, Chinese financial markets (overwhelmingly by Hong Kong SE) are influential on foreign exchange markets and an increase in the volatility in both Chinese financial markets is spread around other markets significantly.

6.3. Effects of Foreign Markets to Industrial Production Growth of China

The last part deals with the channel which is defined to be the impact from a financial volatility to production growth of China. The basic intuition behind this chapter is that a negative impact on volatility of foreign markets might result in a deterioration in demand channel suggesting a fall in consumption, and hence trade potentials might be negatively affected. Therefore, a shock in foreign developed markets might cause Chinese production growth to slow down. The results from generalized variance decomposition and impulse responses provide us some evidence about this channel –negative impact on Chinese production growth caused by financial volatility in foreign markets. First of all, sign restrictions are 8% of 10.000 trials, as shown below. Moreover, under generalized variance decompositions tables we observe that the highest percentage affecting Chinese production growth belongs to domestic channels. But the biggest contribution comes from the US by 2.5%. Overall, Chinese production growth is found to be severely affected from its domestic dynamics.

Figure 9: Generalized Variance Decomposition from All Other Variables to Chinese IP Growth

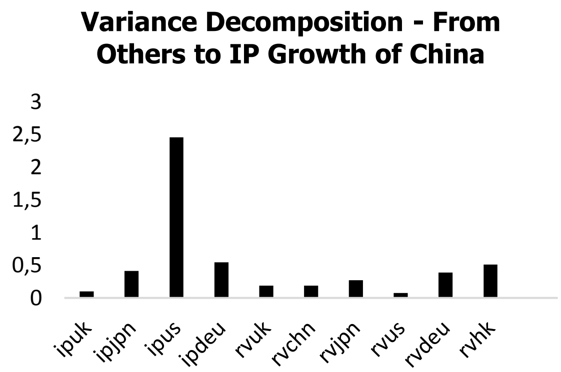
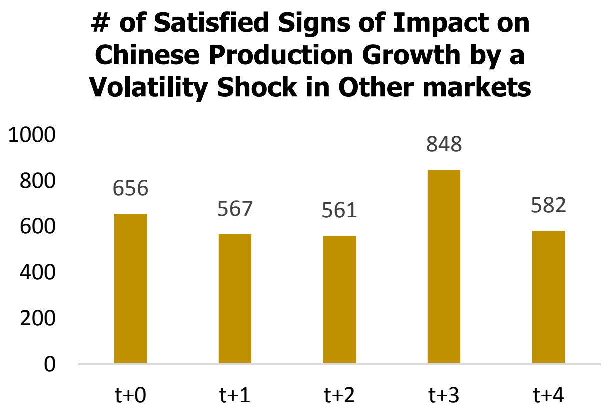


Figure 10: Number of Successful Other Countries' Volatility-to-Chinese IP Growth Sign Restrictions



From either Japan or the UK, there is indeed little effect although in impulse response we observe a fall in the growth rate at t+1 and especially at t+4. Although we find that the impact from a turmoil in foreign financial markets on Chinese production growth is relatively less crucial compared to the first two hypotheses we made, there is still some evidence in favor of our restriction. Generalized Impulse Responses do reflect a similar pattern (see Table P2, Appendix A).

7. CONCLUSION

In conclusion, our results suggest that there is a very close relationship among developed countries in terms of both industrial production growth and volatility considering sign restrictions, impulse responses and generalized variance decompositions. This might be due to the fact that there is a world business cycles as stated in Kose et al.(2003). Moreover, we find that China has a disaggregated financial and production markets, i.e. a shock in Chinese stock markets have little impact on its production growth. Secondly, we observe that Hong Kong Stock Exchange has great impacts on other financial markets. Lastly, a shock in a foreign developed market does not have a huge impact on Chinese industrial production growth. We find that a turbulence in the US financial markets has the highest ramification on Chinese production. That might be due to the deterioration in the trade channel. Also, we observe that China is still vastly affected from its domestic conditions more than a turbulence in the world in terms of production side. Our results might be expanded via two different approaches. First of all, a before-2008 and after-2008 analysis might be investigated, which we could not do so due to the problem of degrees of freedom. Secondly, the number of countries might be increased such that more emerging markets and Asian markets might be included so that the investigation on China and other markets could be sharpened considerably. Lastly, trade channel could be taken into account so that Chinese domination in export and imports could best be observed.

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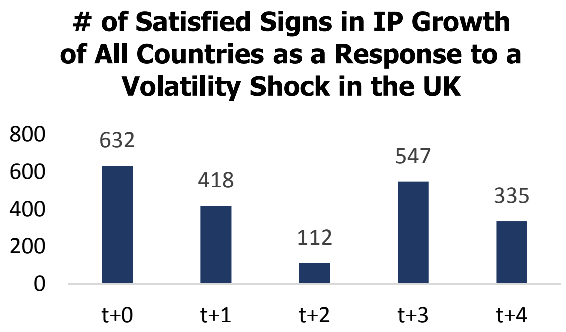
APPENDIX A

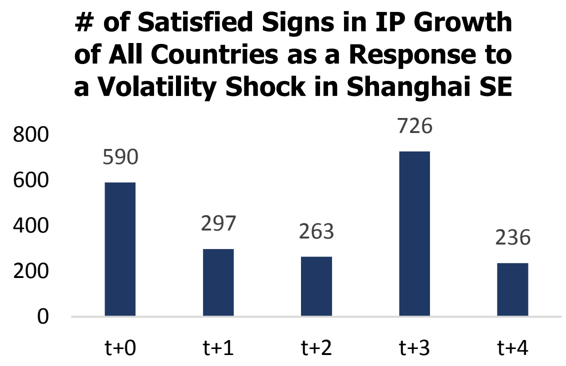
TABLE K: 1% and 5% Critical Dickey-Fuller tau values for unit root tests

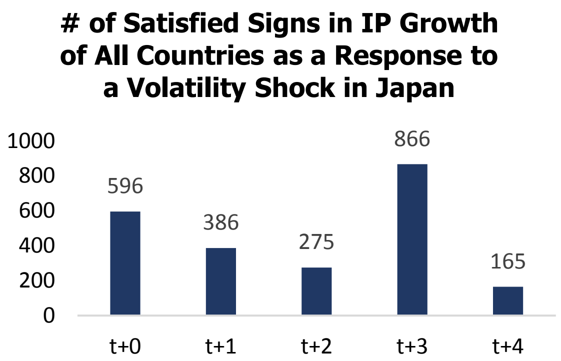
Sample Size	**Tau – No Constant**		**Tau –Constant**		**Tau –Const&Trend**	
	1%	5%	1%	5%	1%	5%
25	-2.66	-1.95	-3.75	-3.00	-4.38	-3.60
50	-2.62	-1.95	-3.58	-2.93	-4.15	-3.50
100	-2.60	-1.95	-3.51	-2.89	-4.04	-3.45
250	-2.58	-1.95	-3.46	-2.88	-3.99	-3.43
500	-2.58	-1.95	-3.44	-2.87	-3.98	-3.43
∞	-2.58	-1.95	-3.43	-2.86	-3.96	-3.41

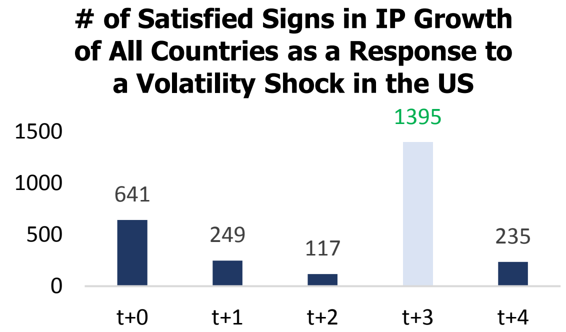
Source: Gujarati

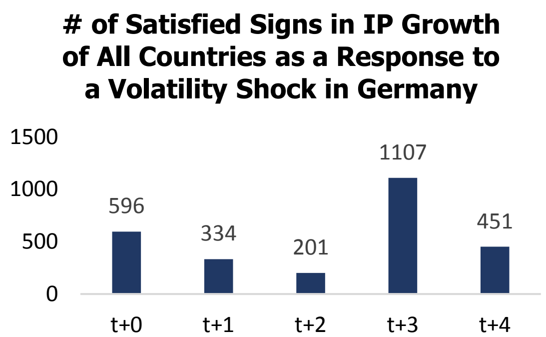
TABLE R1: Volatility Shock to Industrial Production Growth at time interval [0,4] out of 10.000 trials











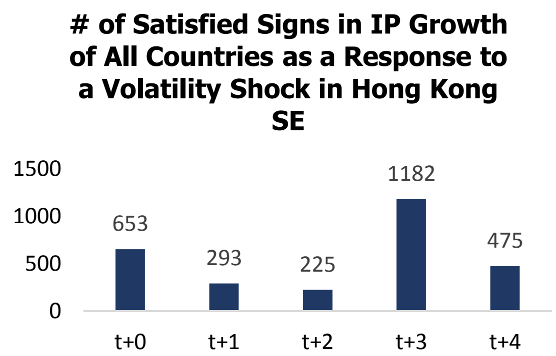
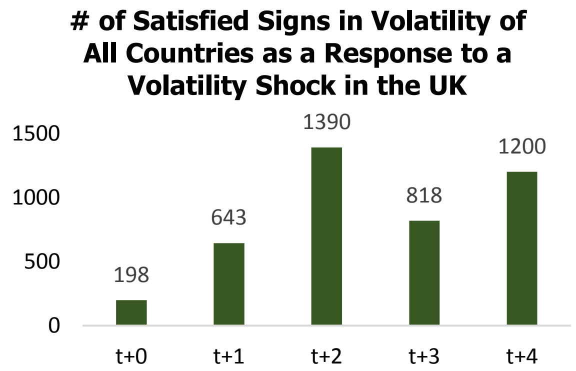
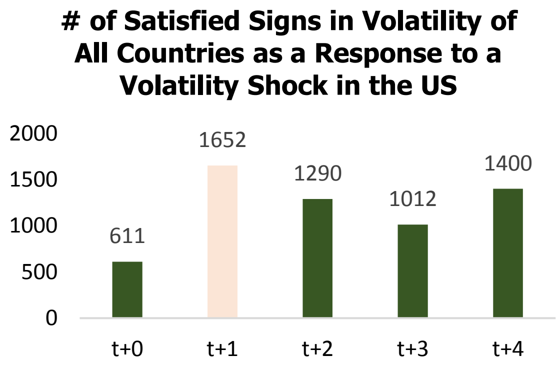
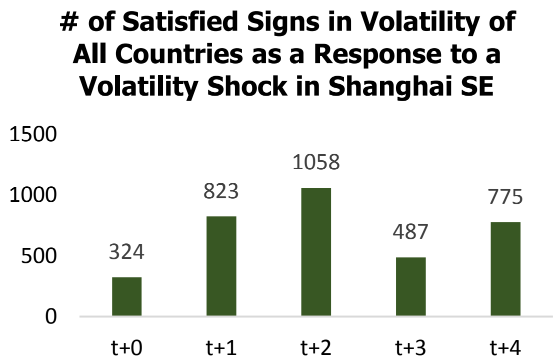
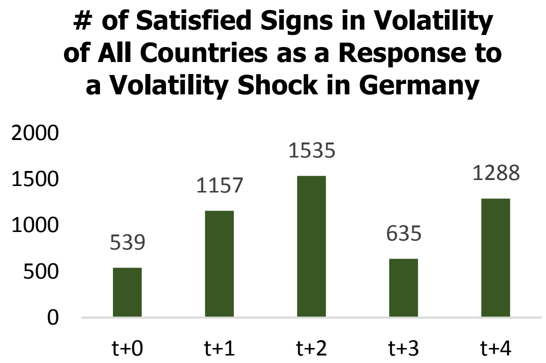


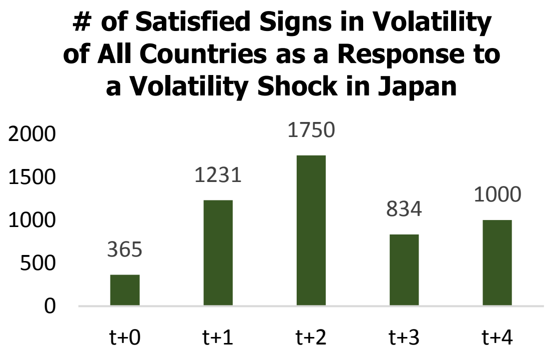
TABLE R2: Volatility Shock to Volatility at time interval [0,4] out of 10.000 trials











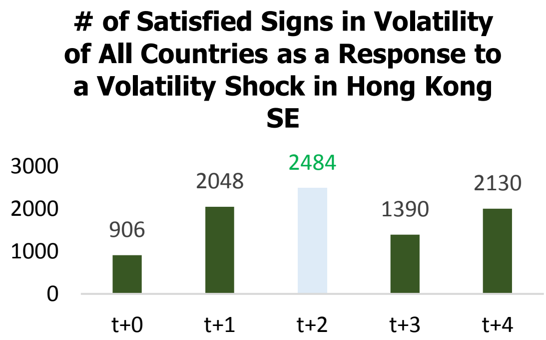


TABLE V1: Generalized Variance Decompositions – t+2

VAR.D.	IPUK	IPCHN	IPJPN	IPUS	IPDEU	RVUK	RVCHN	RVJPN	RVUS	RVDEU	RVHK
IPUK	90.76	0.14	4.32	1.51	3.02	0.06	0.02	0.00	0.04	0.09	0.04
IPCHN	0.10	95.13	0.42	2.21	0.56	0.19	0.19	0.24	0.08	0.38	0.51
IPJPN	5.52	0.45	85.19	1.49	3.90	0.27	1.60	1.43	0.04	0.08	0.03
IPUS	0.97	1.99	9.44	83.57	2.47	0.47	0.18	0.31	0.44	0.08	0.07
IPDEU	3.53	0.49	7.02	2.50	77.06	0.40	0.18	0.43	3.38	1.90	3.11
RVUK	0.01	0.04	0.16	0.24	0.25	47.91	0.98	3.39	24.08	13.31	9.63
RVCHN	0.00	0.13	1.69	0.03	0.11	1.02	89.95	1.25	0.02	0.99	4.82
RVJPN	0.01	0.05	1.58	0.03	0.43	4.95	1.01	74.87	6.12	5.05	5.89
RVUS	0.02	0.05	0.01	0.14	1.85	23.70	0.08	3.80	44.32	15.44	10.60
RVDEU	0.06	0.13	0.18	0.03	1.17	15.91	0.52	3.50	17.70	48.95	11.86
RVHK	0.17	0.21	0.00	0.01	2.11	9.65	4.22	4.30	11.38	13.07	54.87

TABLE V2: Generalized Variance Decompositions – t+3

Column1	IPUK	IPCHN	IPJPN	IPUS	IPDEU	RVUK	RVCHN	RVJPN	RVUS	RVDEU	RVHK
IPUK	90.30	0.17	4.53	1.75	3.00	0.06	0.02	0.01	0.04	0.08	0.04
IPCHN	0.10	94.86	0.42	2.46	0.55	0.19	0.19	0.27	0.08	0.39	0.51
IPJPN	5.46	0.47	84.35	2.31	3.97	0.27	1.59	1.42	0.04	0.08	0.03
IPUS	2.12	1.72	8.20	71.60	3.00	3.06	0.87	3.31	2.89	1.65	1.58
IPDEU	4.05	0.50	6.76	3.11	73.73	0.65	0.18	1.36	3.64	2.64	3.37
RVUK	0.01	0.06	0.15	0.69	0.25	46.69	1.12	3.45	24.15	13.46	9.96
RVCHN	0.00	0.13	1.67	0.03	0.11	1.09	89.38	1.29	0.04	1.07	5.19
RVJPN	0.02	0.07	1.60	0.04	0.44	4.96	1.01	74.74	6.13	5.06	5.94
RVUS	0.03	0.05	0.01	0.13	1.83	23.53	0.19	3.82	42.98	16.37	11.05
RVDEU	0.07	0.13	0.17	0.03	1.21	16.17	0.58	3.53	17.76	48.18	12.17
RVHK	0.16	0.22	0.04	0.01	2.10	9.95	4.63	4.32	11.47	13.03	54.07

TABLE V3: Generalized Variance Decompositions – t+4

Column1	IPUK	IPCHN	IPJPN	IPUS	IPDEU	RVUK	RVCHN	RVJPN	RVUS	RVDEU	RVHK
IPUK	89.81	0.22	4.55	1.75	3.03	0.15	0.03	0.10	0.14	0.14	0.08
IPCHN	0.22	94.45	0.51	2.61	0.55	0.19	0.20	0.29	0.08	0.39	0.51
IPJPN	5.48	0.47	83.72	2.33	3.98	0.37	1.59	1.51	0.15	0.19	0.21
IPUS	2.09	1.73	8.28	71.31	2.99	3.01	0.87	3.30	2.86	2.00	1.55
IPDEU	3.97	0.59	6.92	3.22	73.07	0.73	0.26	1.46	3.71	2.65	3.42
RVUK	0.01	0.07	0.17	0.83	0.27	46.16	1.19	3.48	24.10	13.48	10.24
RVCHN	0.00	0.14	1.66	0.03	0.10	1.13	89.09	1.31	0.06	1.12	5.36
RVJPN	0.02	0.10	1.62	0.04	0.44	4.96	1.01	74.65	6.13	5.06	5.96
RVUS	0.03	0.05	0.02	0.19	1.80	23.57	0.24	3.84	42.62	16.43	11.22
RVDEU	0.07	0.12	0.17	0.07	1.18	16.45	0.61	3.56	17.93	47.57	12.26
RVHK	0.15	0.21	0.09	0.04	2.03	10.08	5.05	4.31	11.51	13.04	53.48

TABLE P1: Generalized Impulse Response of IP Growth of China to Others

Response to Generalized One S.D. Innovations ± 2 S.E.

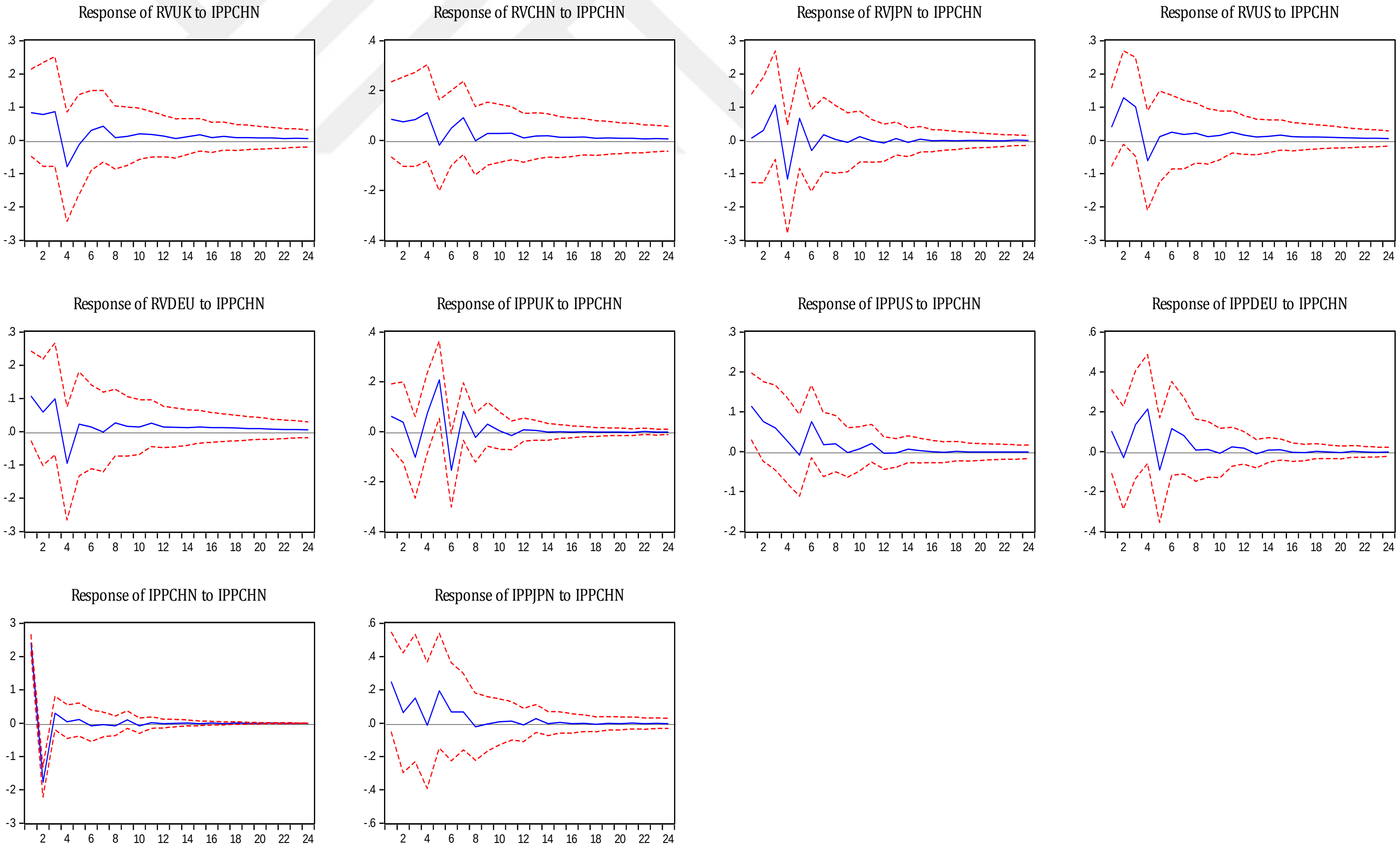


TABLE P2: Generalized Impulse Responses of IP Growth of All to Volatility Shock in Other Markets

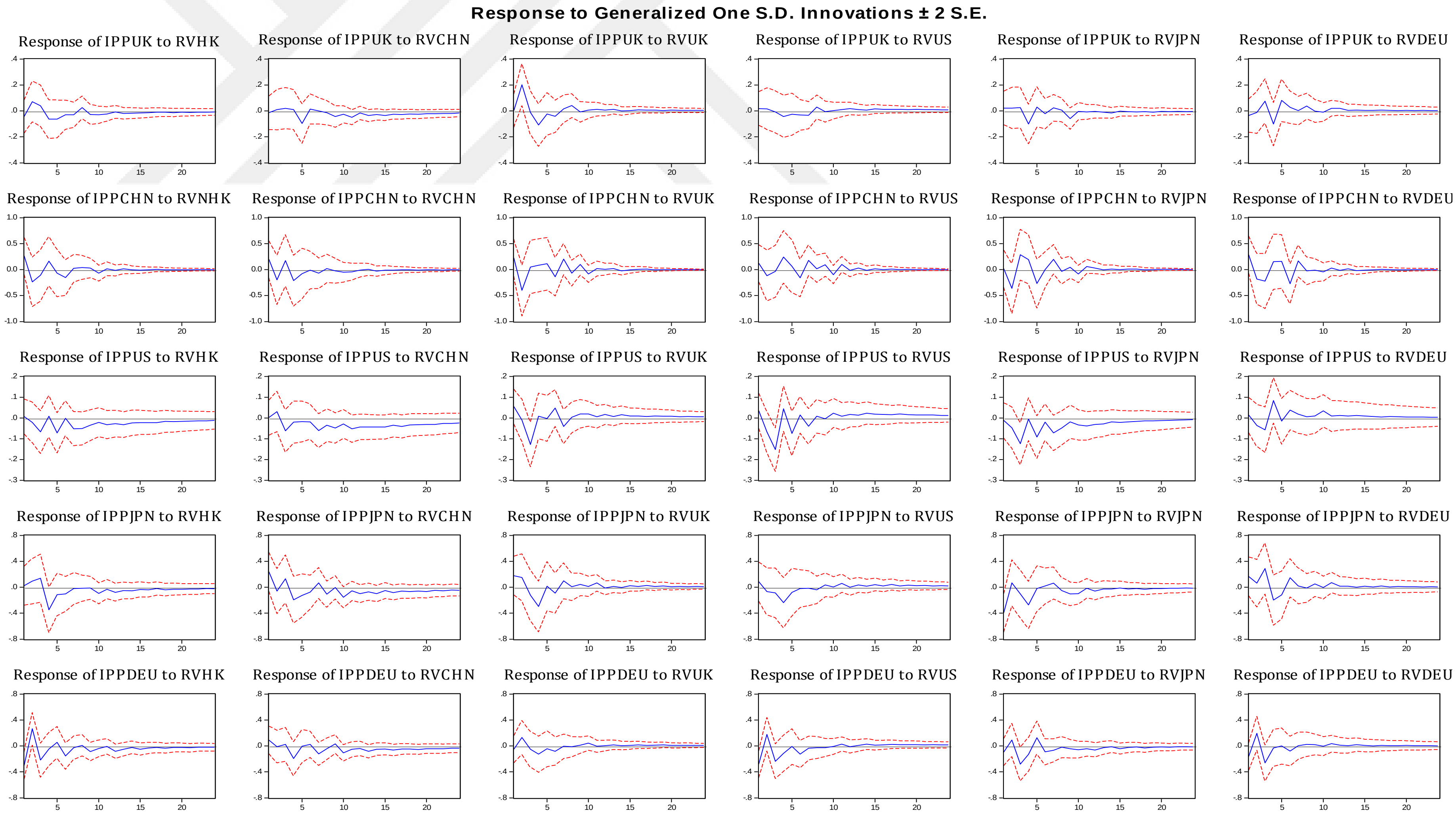


TABLE P3: Generalized Impulse Responses Volatility of All to Volatility Shock in Other Markets

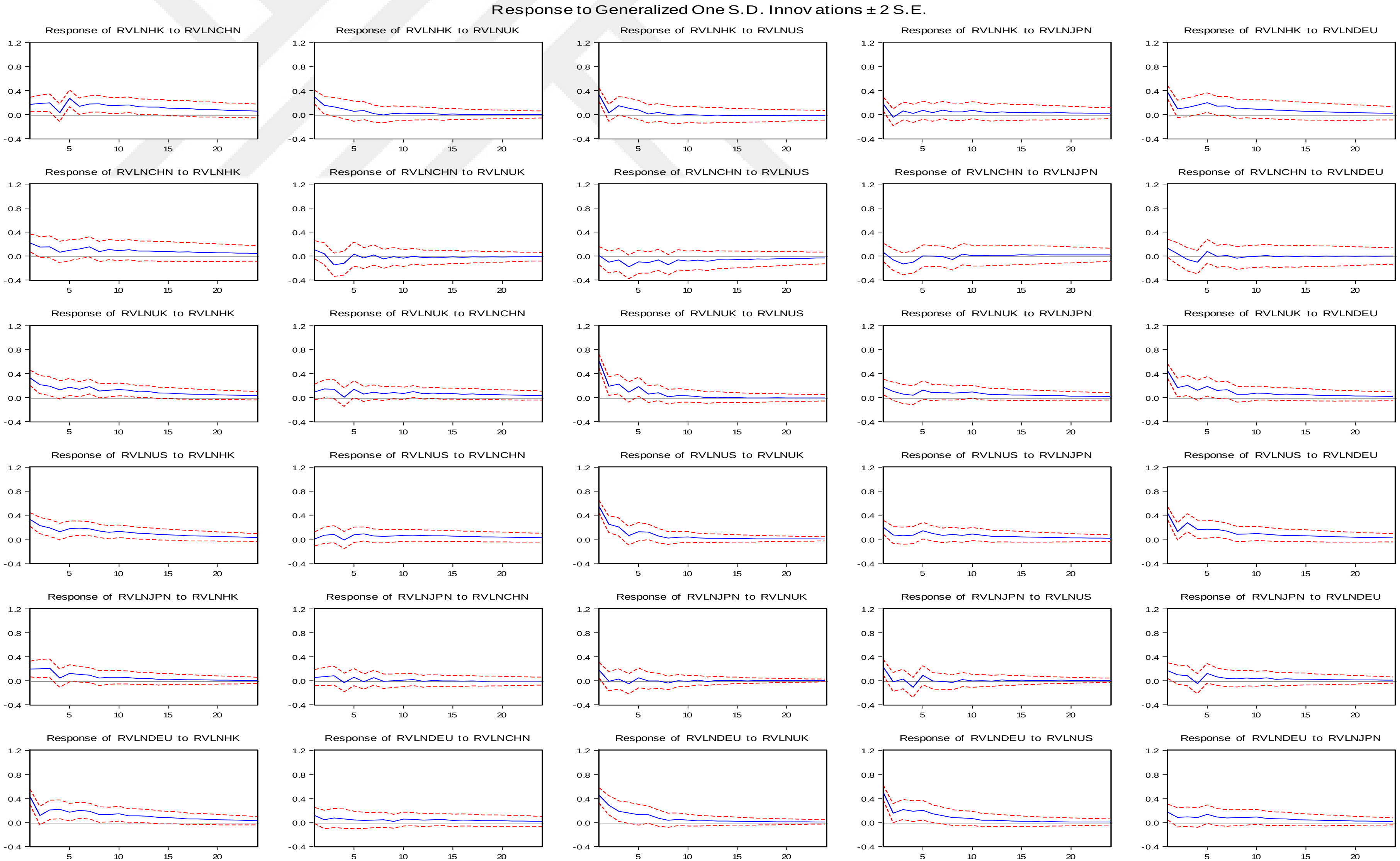


TABLE P4 –Generalized Impulse Responses IP Growth of All to IP Shock in Other Markets