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The effects of macroeconomic variables on Asian stock market volatility: A GARCH MIDAS approach

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ABSTRACT

This paper aims to investigate the effects of macroeconomic variables on stock market volatility in three Asian countries by applying GARCH MIDAS model. The study covers the period from 01/2003 to 06/2014. The GARCH MIDAS framework allows to incorporate macro variables directly in the model and obtain long-term and short-term volatility separately. Empirical findings show that some macroeconomic variables significantly affect stock market volatility. While Chinese and South Korean stock market reacts to either inflation or industrial production growth information, Japanese stock market is sensitive to both factors. In addition, macroeconomic factors influence three markets at different magnitude. The results also indicate that three markets behave differently to the same factors. Real oil price shock stems from aggregate demand significantly lowers Japanese stock market volatility. In contrast, South Korean and Chinese stock market volatility is positively influenced by the same shocks.

Keywords: China, South Korea, Japan, stock market, volatility, GARCH MIDAS, inflation, industrial production, oil price shocks.

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1. INTRODUCTION

This chapter provides general statements about the relationship between macroeconomic variables and stock market volatility. Besides that, I motivate the objective as well as contributions of the study. Finally, the thesis outline is presented.

The relationship between stock market volatility and macroeconomic variables has been investigated for a long time. For example Schwert (1989) found weak effects of macro fundamentals on US stock market volatility. Liljeblom and Stenius (1997) linked Finish stock market volatility to inflation and industrial production index. Kearney and Daly (1998) examined the relationship between macroeconomic variables and Australian stock market. This interest stems from the importance of stock market in economy. It acts as a barometer and predictor of economy's health. Through activities of market participants, funds are mobilized and reallocated effectively to drive economic growth. Stock market volatility plays an important role in investors' decisions in allocating their assets and risk management. Besides that, policy makers also pay special attention to stock market volatility since their target is to stabilize stock market in order to improve the effectiveness of market.

There are three background theories that are able to explain for this relationship. First is arbitrage pricing theory proposed by Ross (1976), where asset returns are supposed to depend on multiple factors. Second is discounted cash flow model which assumes that current stock price is the discount of future cash flow. Finally is volatility asymmetry model. These three models suggest that any factor affects future cash flow or discount factor will have influence on stock prices. Similarly, factors that cause uncertainty in future cash flow and discount factor, will impact stock returns volatility.

The purpose of this study is to test whether macro variables can explain stock market volatility in East Asian countries. I focus on three key factors namely, inflation rate, industrial production and oil price shocks. While inflation and industrial production are different among countries, oil price shock is used as common factor for all countries. By this way, it is able to explore reactions of stock market to both specific and common factors. Since each market has its own characteristics, they are expected to behave differently with the same factors in accordance with particular economic situations. The study employs GARCH MIDAS model, proposed by Engle, Ghysels and Sohn (2008) for the period 2003-2014.

In recent years, Asia is of particular interest because of its role in global economy. Asia is forecasted to be the main driver of global economy growth in near future. Hence, foreign investors consider Asia as an attractive market to expand and diversify their portfolios. Despite the fast growth of some Asia countries such as Vietnam, India, Malaysia, three East Asian economies: Japan, China and South Korea are in dominant positions in the region. Japan is the third biggest economy in the world. After impressive growth since 1960s until 1980s, Japan economy entered into the period of downturn and deflation. Recent events such as the Asian currency crisis in 1997, the global recession in 2008 and effects of natural disasters prevent Japan from recovery. Similar to Japan, South Korea also experienced a long time of fast economic growth until early 2000s. Like other economies, South Korea economy slowed down in 2008 and 2009 due to effects of global financial crisis. However, this economy bounced back soon thanks to government stimulus packages. In comparison with Japan and South Korea, China started its economic boom later. Nevertheless, it is still expanding and growing with impressive rate. Despite the effects of global crisis, China maintained economic growth of above 5% in 2008 and 2009[1]. China is now ranked second largest economy in the world behind the US and has the most influence on global economy. In contrast to fast growth of economic, financial market and stock market in China and South Korea are lagging behind overall economic developments. These two immature markets have some specific characteristics compared to other developed markets. It comes from the differences in regulatory and market participants. Retail investors, who are less sophisticated about trading, dominate these two markets. Therefore it should not expect these markets behave in line with theories.

Inflation and industrial production growth reflect the change of price and output. They are key determinants of stock markets. Oil also takes crucial role in the development of these countries. It is the input of almost industries. As a result, any change in oil price should have effects on economic and financial markets. It is extremely important for China, Japan and South Korea since they are top consumers of oil in the world. According to the US Energy Information Administration[2], South Korea is the fifth largest importer of crude oil. China with its giant economy is the second largest net oil importer and oil consumer. It is forecasted to surpass the US to become the biggest net importer in near future. China oil demand accounts for a third of total global demand in 2013. Japan stands right behind China as the third-largest oil consumer and importer. While China can produce oil and liquid productions to serve its domestic demand partly, Japan and South Korea oil demand relies largely on import due to

[1] National Bureau of Statistic of China. Tradingeconomics. [online] Available at: http://www.tradingeconomics.com/china/gdp-growth-annual [Accessed 10 April 2015].
[2] EIA, 2013. US. Energy Information Administration. [online] Available at: http://www.eia.gov/ [Accessed 10 April 2015].

limitation of domestic resources. Therefore oil price shock is believed to have power in explaining stock market volatility in these countries.

The paper contributes to existing literatures in different aspects. First, almost researches on the linkage between stock market and macro variables in East Asia are conducted for the level of macro fundamentals and stock returns. This study sheds light on the effects of both macroeconomic level and volatility on stock market volatility. Second, the GARCH MIDAS is applied to allow for incorporating macro variables directly into models. Hence the loss of efficiency due to multiple steps estimation is reduced. In addition, GARCH MIDAS model provides a clearer picture about contributions of short term and long term component to daily stock volatility. Finally, this paper follows Killian (2009) to decompose real oil price shocks into three components, namely aggregate demand shock, specific demand shock and supply shock. Therefore we can observe how each component shock influences stock market volatility.

The thesis is structured as below: Section 2 presents some theoretical backgrounds. Section 3 reviews some relevant literatures about the linkage between stock market volatility and macro variables. Methodology is presented in section 4. Section 5 describes data collection and summary statistic. Empirical findings is presented and discussed in section 6. My thesis ends with conclusion in section 7.

2. THEORETICAL BACKGROUND

In this part, I introduce three models which are believed to have ability to link macroeconomic variables to stock market volatility. They are Arbitrage pricing model developed by Ross (1976), future cash flow discounted model and volatility asymmetry model.

2.1. Arbitrage pricing theory

Arbitrage pricing theory is considered as an extension of capital asset pricing model (CAPM) proposed by Sharpe (1964). It is first introduced by Ross (1976). In the CAPM model, asset returns are assumed to depend on system risk of market portfolio. However, this assumption is relaxed in APT model, where a group of multi factors such as economic indicators, financial information have influence on asset returns simultaneously. The APT model can be expressed as below:

$$r_i = E_i + \beta_0 + \beta_1 f_{i1} + \beta_2 f_{i2} + \cdots + \beta_k f_{ik} + \varepsilon_i \quad (1)$$

Where r_i is the return of asset i, E_i is expected return, β_0 is risk free rate of return, β_i is the coefficient of factor loadings, f_{ik} is macro factor and ε_i is the nonsystematic risk. In relative to CAPM model, the APT model is more powerful in reflecting real economic activities since it allows users to identify the impact of influenced factors separately. Particularly, there can be understood exactly to what extent and direction particular factor drives asset returns. Due to its effectiveness and convenience, many researches have been carrying out based on this model[3].

2.2. Future cash flow discounted model

Another framework to link macro factors with stock market is discounted cash flow model. The model can be expressed as below:

$$P_t = \frac{E_t[D_{t+1}]}{1+E_t[r]} + \frac{E_t[P_{t+1}]}{1+E_t[r]} \tag{2}$$

Where $E_t[D_{t+1}]$ is the expected dividend at time t+1

$E_t[P_{t+1}]$ is the expected of the stock price at time t+1

$E_t[r]$ is the expect discount factor or cost of capital

Since stocks are more risky than bonds, equity holders who are risk averse require higher rate of return. This is reflected in the discount factor which is the composition of interest rate and risk premium. Equation (2) can be interpreted that value of stock at time t equals present value of expected dividend and expected stock market value at time t+1. This condition is hold for all periods. We therefore have formula in period t+1:

$$P_{t+1} = \frac{E_{t+1}[D_{t+2}]}{1+E_{t+1}[r]} + \frac{E_{t+1}[P_{t+2}]}{1+E_{t+1}[r]} \tag{3}$$

By substituting P_{t+1} in (2) by P_{t+1} in (3) recursively we get:

$$P_t = \sum_{i=1}^{n} \frac{E_t[D_{t+i}]}{(1+E_t[r])^i} + \frac{E_t[P_n]}{(1+E_t[r])^n} \tag{4}$$

As T→ ∞, (2) becomes:

$$P_t = \sum_{i=1}^{\infty} \frac{E_t[D_{t+i}]}{(1+E_t[r])^i} \tag{5}$$

[3] See for example Huberman (2005); Lehmann and Modest (1998)

Above formula tells us that stock price depends on future cash flow and discount factor. From this model, we can conclude that any factor that have effects on future cash flow or discount factor will have effect on stock price. Since discount factor is the sum of interest rate and risk premium, any shocks on these two factors will also drive stock price and volatility. It is noted that different news will impact discount factor and future cash flow differently. Some shocks decay quickly, some last for couple of years. Similarly, volatility of stock return also depends on the uncertainty of the future cash flow or discount factor.

2.3. Volatility Asymmetry

Volatility asymmetry is a phenomenon which is observed and documented in financial markets especially on equity markets. The theory states that negative shocks induce financial time series more volatile than positive shocks do (Chris, 2008). There are two main reasons contribute for this phenomenon. First is hypothesis of leverage effect. Black (1976) and Christine (1982) are the firsts who explain volatility asymmetry based on leverage effect. If there is a bad news leads to an increase in discount factor or decrease future cash flow, stock price will fall. As a result, equity ratio which is measured by the ratio between debt and market value of equity will rise. Higher leverage ratio implies that stocks are risker and more volatile. The other reason is volatility feedback or time varying risk premium hypothesis. According to this hypothesis, volatility of stock will be reflected in price movement. Particularly, when stocks experience high volatility, investors will require higher return. In order to achieve this target, current stock price would decline. Although both hypotheses explain dynamic negative correlation between return and volatility, they are different in term of direction. The leverage effect says that high volatility take a root from reduction of stock price. In contrast, volatility feedback hypothesis assumes that stock price is impacted by stock volatility. Various studies examine about this phenomenon and confirm the existence of asymmetric volatility in financial markets (Schwert, 1989; Nelson, 1991; Reyes, 2001).

2.4. Macroeconomic determinants of stock market volatility

Given above theories, macroeconomic variables influence future cash flow or discount factor, may have impact on stock volatility. However these theories are impossible to assure whether one variable relates negatively or positively to stock market volatility. All factors are interdependent. Besides that the direction and magnitude of effect vary according to the persistence of factors and states of economy.

Economic activity is believed to have great effects on stock market volatility. It is well represented by industrial production index which measures output of majors or all business and economic sectors such as manufacturing, mining, construction, etc. High industrial production is considered as a good signal for stock market during recession and stable periods. An increase of industrial production improves firms' expectation about future. This motivates them to produce more, expand the markets. As a result, revenue, profit and stock price are higher. Another positive effect of high industrial production to stock market is through the risk premium. Growth in industrial production can be interpreted as a stable economic environment. Investors translate it as a signal to increase their investments and require lower risk premium. On the other hand, if industrial production is greater than expectation during overheating periods, it raises a fear of rising interest due to tight monetary policies. This induces stock price to fall and increase stock market volatility.

Another factor investigated extensively is inflation. Inflation is the rise of price level from time to time. It is the goal of monetary policy of almost governments and central banks. Governments aim to manipulate economic growth by influencing inflation. It is extremely important for countries who suffer abnormal inflation rate such as too high inflation or deflation. Inflation may affect stock market directly or indirectly. It is often assumed to have negative effect on stock market. The first negative effect of inflation on stock market is through the tax effect. It is widely accepted that tax liabilities is an increasing function of inflation. Inflation may also have direct impact to firms' cash flow. Fischer and Modigliani (1978) documented the influence of inflation on cost of capital, firm market value, investment decision. Higher inflation is associated with higher cost of goods and services. However it takes longer time for firms to adjust sale price. Consequently, profit and therefore stock price will decline. Another hypothesis on the negative impact of inflation to stock market is Fisher effect. Fisher (1930) suggested that nominal interest rate moves one to one in the same direction with inflation. Such that central bank will increase interest rate in order to fight against inflation. Since interest rate appears in the discount factor, high inflation will have negative effect to stock market according to equation (5). However there is argument that future cash flow also benefits from high inflation. If this is the case, then negative effect of inflation will be neutralized by an increase in future cash flow. Nevertheless future cash flow tends to rise with different rate compared to inflation. Inflation also has indirect effect through economic activity. This issue is examined in some papers. Hasanov and Omay (2011) found that stock market performance is affected by inflation since it causes fluctuation of future inflation and real economic activity. Not only is level of inflation on interest but also the volatility of inflation is. Judson and Orphanides (1999) concluded that economic growth is significantly affected by both inflation level and volatility.

The influence of oil price shock on stock markets depends on whether countries are oil imported or exported. For net import countries like South Korea, Japan and China, a shock to oil prices is believed to have negative effect on stock market. First, oil is crucial input for many industries. An increase in oil price results in higher cost of production. Unless this additional cost is passed to consumers by raising sale price, firms' profit and cash flow will decline. Oil price also has indirect effect on stock market through inflation. It is important factor contributes to the rise of inflation especially for oil dependent countries. However Kilian and Park (2009) criticized that this is not always the case. Oil price shock may have positive effect if it stems from aggregate demand. An increase in global demand for commodities requires higher oil demand. This in turn raises the oil price. Nevertheless aggregate demand also increases output and firms' expectation and therefore cash flow. If the positive effect dominates the negative effect, stock market will benefit from oil price shocks. It is especially important for three East Asian countries since all of them are export-oriented countries. They involve deeply in global economic activities. Additionally, oil price shock stems from aggregate demand also has positive effect to stock market through the discount factor. It reduces risk premium thanks to stable economic environment.

3. LITERATURE REVIEW

This part provides reviews about relevant literatures about the relationship between stock market volatility and macro fundamentals. Since industrial production and inflation are usually investigated together, the review is combined for them. I also provide review on the effect of oil price to stock market and the GARCH MIDAS framework in modelling stock market volatility

3.1. Effects of industrial production and inflation on stock market volatility

It has been nearly three decades since the first research on the effect of macroeconomic variables on stock market volatility conducted by Schwert (1989). In this paper, Schwert used four variables including inflation and industrial production to prove that stock market fluctuation can be explained by macro fundamentals to some extent. He documented that inflation shows little evidence of its impact to stock market volatility except the period from

1953 to 1987. The same result was also revealed for industrial production factor. Liljeblom and Stenius (1997) conducted similar study for Finish stock market. Their result is in contrary with prior study of Schwert, shows stronger influence of macroeconomic variables. Empirical findings show that 43% to 50% of stock market volatility can be contributed by macro variables. Their study offers more contributions by estimating both individual and joint contribution of different variables. For separate models, inflation and industrial production growth are not significant for all periods. However all of them have positive significant coefficients in joint models except for inflation, which has negative sign in the sample from 1970 to 1991. Kearney and Daly (1998) employed GLS method to link Australian stock market volatility to five macro variables. Empirical results show that inflation contributes to stock market volatility directly, while the effect of industrial production is indirect. In order to find international evidence of relationship between stock market volatility and macro factors, Errunza and Hogan (1998) employed VAR model to study for seven European countries. They found that UK, Switzerland and Belgium markets are silent to all macro information. Meanwhile, money supply is proved to affect Germany and France stock markets. In contrast, the uncertainty of real economic activity in Italia and Netherland is reflected in stock market movement.

The relationship between stock market volatility and macro variables is examined not only for developed markets but also for developing markets. Since these markets are immature and have different characteristics with developed markets, macro information is reflected ineffectively. Chinzara (2011) conducted research for South Africa market. He documented that inflation statistically influences stock market volatility. Industrial production does not bear any information about stock market volatility. Olweny and Omondi (2011) applied EGARCH and TGARCH model to analyze the linkage between macro factors and stock market in Kenya for 10 years periods from 2001 to 2010 based on monthly data. Their results show that exchange rate, inflation and interest rate statistically affect stock market volatility. In Malaysia, Zakaria and Shamsuddin (2012) employed VAR mode to explore causal relationship between stock market volatility and five variables, namely GDP, inflation, exchange rate, interest rate and money supply. They came to conclusion that there exists very weak relationship between stock market volatility and macroeconomic volatilities. Attari et al. (2013) related volatility of Pakistan stock market to three variables including inflation and gross domestic product (GDP). The EGARCH model is applied with monthly data from 1991 to 2012. Their results support for Zakaria and Shamsuddin (2012). GDP insignificantly causes stock market volatility. In contrast, inflation volatility weakly granger causes stock market volatility at 10% level of significance.

In East Asia, some researches have been conducted for this relationship. However most of researches are done for stock return instead of its volatility. Mukherjee and Naka (1995) employed VECM model to explain causal relationship between Japanese stock market and six macro factors, exchange rate, inflation, money supply, real economic activity, long term government bond rate and call money rate for the high growth period from 1971 to 1990. They found that exchange rate, industrial production index, money supply have positive effect on stock market index. On the other hand, an increasing in inflation rate leads to a fall in stock price. In an attempt to find determinants of long term Japanese stock market movement, Humpe and Macmilan (2009) used the same model with Mukherjee and Naka (1995). They concluded that industrial production and money supply are priced in stock market in opposite directions. Surprisingly, they found no evidence of existence relationship between inflation, discount rate and Japanese stock market. The same approach was employed by Kwon and Shin (1999) to investigate whether macro information are priced in South Korean stock return for the period from 1980 to 1992. They documented that macro information is reflected in stock market price. In comparison with US and Japan markets, South Korean stock market investors have different perception as those in developed markets. They also pointed out that macro information is conveyed to stock market with some lags. Chen, Fang and Zhang (2012) used monthly data for 9 years period to explore the effect of monetary and fiscal policies on Chinese stock market by GARCH type models. Their research showed that fiscal policies do not statistically influence stock market conditional volatility. However, combination of fiscal and monetary policies can drive stock market movement.

3.2. Effects of oil price shocks on stock market volatility

Researches on oil price shocks and stock market correlation have been carried out for many years. Different conclusions have been given. Some support for the existence of relationship between stock market and oil price shocks (Papapetrou, 2001; Sadorsky, 1999; Ratti and Hasan, 2013; Masih, Peters and De Mello, 2011). Some show that oil price does not help to predict stock market movement (Chen, Roll, Ross, 1986; Cong et al., 2008). Park and Ratti (2008) examined this relationship in US and 13 European countries. Their study figured out that oil price has effect on stock returns in US and European countries during the period from 1986 to 2005. However direction and magnitude are different across countries. Increasing of oil price leads to increasing of Norway stock price. However inverse reactions are found in other 12 European countries. Another noteworthy finding is that oil price volatility and stock market volatility in European countries are negatively correlated while it is positive in US.

Above studies based on assumption that oil price shocks is exogenous variable. This means that there is only one direction effect from oil price shock to macro variables or stock return but there does not exist opposite direction. Kilian (2009) criticized this approach in his paper "Not all price shocks are alike: Disentangling demand and supply shocks in the crude oil market". He argues that there is causal effect between macroeconomic and oil price shocks. Hence it is unreasonable to treat oil price shock as exogenous variable. In addition, he suggests that global demand may have influence on oil price. In order to capture the underlying source effect of different oil price shocks to US economy, oil prices shocks are decomposed into three components, namely: aggregate demand shocks, oil supply shocks and specific demand shock. Aggregate demand shock reflects global real economic activity, measured by dry cargo freight rate. Specific demand arises from a fear of shortfall of oil supply in the future. Using VAR model, he showed that each component has different effect to economic activities. The most worthy conclusion is that real oil price shocks are mainly contributed by aggregate demand shocks and specific demand shocks. Oil supply shocks hardly provide information about real oil price shocks. Based on this idea, numerous researches have been conducted to investigate how these components drive the movement of stock market. Abhyankar, Xu and Wang (2013) used VAR model to investigate the effect of different oil price shocks to Japanese stock market for the period 1988-2009. Empirical evidence showed that the change in aggregate demand has positive correlation with Japanese stock returns. In contrast, oil price shocks arise from precautionary demand has negative effect. Oil supply shock is not significant in explaining stock market returns. Fang and You (2014) used monthly data from 2001 to 2012 to explore the influence of oil price shocks to three economies China, India and Russia. Their findings showed that oil supply shocks insignificantly explain stock returns in China and India. In addition, India stock market always reacts negatively to oil price shocks no matter it is driven by global demand or precautionary demand. Similar result was given for Russian stock market. China stock market has no correlation with global demand shocks.

3.3. Stock market volatility and GARCH MIDAS model

Volatility is one of the most important concept in finance. It tells us about the uncertainty or risk of financial assets. Financial series bear a widely accepted feature called volatility clustering. Volatility clustering is the phenomenon which a large volatility is followed by a large volatility and vice versa. In other words, there is a positive correlation of returns in different periods. This phenomenon violates the assumption of homoscedasticity. In order to account for this problem, Engle (1982) introduced the model called Autoregressive conditional heteroscedasticity (ARCH). In this model, the conditional variance is assumed to depend on past squared of errors. Four year later, Bollerslev (1986) extended the ARCH model to a generalized version called generalized autoregressive conditional heteroscedasticity (GARCH). Unlike the ARCH model, GARCH model allows variance of errors depends on not only the past value of errors but also past value of variance. Therefore, it is called the conditional variance.

Engle, Ghysels and Sohn (2008) argued that "volatility is not just volatility", it is the product of different components. They also emphasized benefits to model these components separately. In an attempt to answer the question of the effect of macro variables to stock market volatility, Engle and Rangel (2008) proposed an idea to divide return volatility into short-term and long-term component, called the Spline-GARCH model. The slowly varying component represents for macro variable which is observed with low frequency while the short-term component is mean reverting GARCH. In comparison with original GARCH model, this model allows conditional variance changes over time. However there exist some drawbacks in this model. First, it cannot include macro variables directly into model. Therefore the estimation has to be done in multiple steps. Consequently, it causes information loss during the estimation process. Engle, Ghysels and Sohn (2008) developed this model by employing new method called Mixed data sampling (MIDAS). MIDAS is introduced by Ghysels, Santa-Clara and Valkanov (2005) which studied the relationship between mean and variance of stock market returns. In their paper, different frequency data are included in the same model. Particularly, daily squared returns are used to predict low frequency volatility. The combination of Spline GARCH model with MIDAS is called GARCH MIDAS. Similar to Spline GARCH model, the volatility is still product of short-term and secular component. The short-term component is mean reverting as Spline GARCH model. However the long term component now reflects information from realized volatility or macroeconomic variables. Engle, Ghysels and Sohn (2008) proposed some advantages of this model compared to conventional approach of Schwert (1989). First, both long-term and short-term component are obtained from regression. Second, macro variables can be linked directly within one step estimation. Engle, Ghysels and Sohn (2008) found that inflation and industrial production growth explain 10% to 35% the daily volatility of US stock returns. Due to these advantages, several papers have been studies based on this model. Asgharian, Hou and Javed (2013), used GARCH MIDAS model, concluded that fundamental information provides some information about stock market volatility. In addition, they documented that including slowly varying component in the GARCH-MIDAS increases prediction ability of the model. Magrini and Dönmez (2013) applied GARCH MIDAS model to find the relationship between macro variables and agricultural commodities. Empirical result showed that macroeconomic activities can be used as a predictor for daily volatility of agricultural commodities. In bonds market, Nieto, Novales and Rubio (2014), employed GARCH MIDAS model, found that macroeconomic and financial indicators can explain secular component volatility of corporate bonds.

4. RESEARCH METHODOLOGY

In this section, I describe about econometric model, GARCH MIDAS and estimation methods.

According to the GARCH MIDAS model stock returns are written as:

$$r_{i,t} = \mu + \sqrt{\tau_t . g_{i,t}} \varepsilon_t, \quad \forall i = 1, \dots, N_t \tag{6}$$

Where $r_{i,t}$ is the return on day i during month t, τ_t is the long term component of volatility and $g_{i,t}$ is the short term component of volatility. Macroeconomic factors which are observed at monthly frequency will have effect on long term component. $\varepsilon_t | \Phi_{i-1,t} \sim N(0,1)$ where $\Phi_{i-1,t}$ represents information set up to day (i-1) of period t. The conditional variance follows GARCH(1,1) process:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{7}$$

Where $\alpha > 0, \beta > 0$ and $\alpha + \beta < 1$. In contrary to method conducted by Schwert (1989) and other conventional approaches which use past values as a measurement of interest, GARCH MIDAS method constructs long term component by weighting function:

$$\tau_t = m + \theta_l \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) X_{t-k}^l \tag{8}$$

In order to avoid negative effect of long term volatility component in estimation process, the log form is employed instead.

$$\tau_t = \exp(m + \theta_l \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) X_{t-k}^{l}) \tag{9}$$

Where K is the number of periods over which we smooth volatility. X_{t-k}^{l} is the level of macroeconomic variables at lag k. The weighting used in equation (X) is described by beta lag polynomial function:

$$\varphi_k(w) = \frac{\left(\frac{k}{K}\right)^{\omega_1 - 1} (1 - \frac{k}{K})^{\omega_2 - 1}}{\sum_{j=1}^{K} (\frac{j}{K})^{\omega_1 - 1} (1 - \frac{j}{K})^{\omega_2 - 1}} \tag{10}$$

Gysels, Santa-Clara and Valkanov (2005) proposed some advantages of this scheme. First, all the weights are positive. Second, the summation of weights equals to one. Third, different values of ω_1 and ω_2 can generate different shapes of weighting scheme: monotonically increasing, decreasing or humped-shaped. Forth, it involves in only two parameters. Therefore the estimation is carried out easily. Finally, different functional form can be tested by changing the order of the polynomial. Weighting scheme can also be used by exponentially weighting as below:

$$\varphi_k(\omega) = \frac{\omega_k}{\sum_{j=1}^{K} \omega_j} \tag{11}$$

Existing literatures have shown that the two methods yield similar results (Engle, Ghysels and Sohn, 2008; Girardin and Joyeux, 2013). Therefore I used beta lag function for my study as it is more flexible. The weights in equation (10) capture the effect of past fundamental information on stock volatility. The larger weight is, the stronger explanatory power is. The goal of the estimation process is to obtain the set of parameters $\Theta = \{\mu, \alpha, \beta, m, \theta, \omega_1, \omega_2\}$. In addition to the level of macroeconomic level, I also want to investigate the effect of second moment of fundamental factors on stock market volatility. This is done via the specification below:

$$\tau_t = \exp(m + \theta_v \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) X_{t-k}^{v}) \tag{12}$$

Where X_{t-k}^{v} is the volatility of macroeconomic variables at lag k. It is noted that the weights of level and volatility are different from each other. Volatility of macroeconomic variables is estimated 12^{th} autoregression. 12 dummy variables are included to allow for different monthly mean:

$$X_t = \sum_{j=1}^{12} \propto_j D_{jt} + \sum_{i=1}^{12} \beta_i X_{t-i} + \varepsilon_i \tag{13}$$

Then squared of residuals of above equation are used as the volatility of macro variables. This measure has been also used by Engle, Ghysels and Sohn (2008), Girardin and Joyeux (2013). Another model specification comes into my consideration is the combination of both level and uncertainty of macroeconomic factors:

$$\tau_t = \exp(m + \theta_l \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) X_{t-k}^l + \theta_v \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2) X_{t-k}^v) \tag{14}$$

The long-term component now reflects both the effect of level and volatility of macro variables on stock market volatility.

The advantage of GARCH MIDAS model is that it allows incorporating different time-spans namely weekly, monthly, quarterly, etc. Due to short estimation period, I decide to use monthly data to assure for sufficient data set. Regarding to the number of lags included in the model, I follow Asgharian, Hou and Javed (2013) and Engle, Ghysels and Sohn (2008) who showed that the optimal weights of the MIDAS equation is 36 lags, or 3 MIDAS years regardless the choice of time-span. Since shapes of weighting scheme depend on values of ω_1 *and* ω_2, there are some alternatives come into consideration to estimate ω_1 *and* ω_2. Asgharian, Hou and Javed (2013) proposed three alternatives:

(i) Estimate both ω_1 and ω_2

(ii) Fix both ω_1 and ω_2

(iii) Fix ω_1 and estimate onlyω_2.

Appendix 4 illustrates beta function for different choices of ω_1 and ω_2. As we can see, beta function is always monotonically decreasing regardless value of ω_2 as long as ω_1 equals to 1. This means that for ω_1=1, closer observations contribute more information to long-term components volatility than older observations do. Therefore it is optimal set ω_1 equals to 1 and let ω_2 is decided by estimation process[4].

[4] This alternative is used in other papers (Asgharian, Hou and Javed, 2013; Girardin and Joyeux, 2013)

My interest is to investigate the effects of macro variables on stock market volatility separately. Thus I model each variable one by one.

The GARCH MIDAS model is estimated by maximum likelihood method (MLE). Wang and Ghysels (2008) stated that the MLE yields a consistent and asymptotically normal estimation for GARCH MIDAS model. In particular, the following log likelihood function is maximized:

$$LLF = -\frac{1}{2}\sum_{t=1}^{T}\left[\log(g_{it}\tau_t) + \frac{(r_{it}-\mu)^2}{g_{it}\tau_t}\right] \tag{15}$$

Since the estimation involves in big set of parameter, it is not always able to get global optimal with conventional optimization method. I follow Asgharian, Hou and Javed (2013) to use the simulated annealing method proposed by Goffe, Ferrier and Rogers (1994). Simulated annealing is the method which is inspired from the heating and cooling process of metal. The simulated annealing algorithm is that it will generate random point at each iteration. If this new point makes the objective smaller than the value of current objective with certain probability, this point will be accepted. Therefore this method allows to achieve global optimal. Asgharian, Hou and Javed (2013) emphasized that "this method is very robust and seldom fails, even for very complicated problems".

5. DATA

5.1. Data collection

I collected daily stock price of three indices KOSPI (South Korea), NIKKEI 225 (Japan) and SSE (China) from 01/01/2003 to 30/6/2014 for my studies. The reason to choose that period is that this period has been studied unevenly despite of its remarkableness. All three countries recovered from the currency crisis in 1997. It also marked a milestone for China when it joined World trade organization in 2001, therefore involves more in global economy. Japan government also started implementing easing monetary to promote economic growth. All stock prices are quoted in local currency to avoid effect of foreign exchange rate. Stock returns are computed by formula.

$$r_t = 100 * ln\frac{P_t}{P_{t-1}} \tag{16}$$

Where P_t and P_{t-1} are stock price at time t and time t-1 respectively. Macroeconomic variables used in this study are measured at monthly frequency. I used consumer price index rather than producer price index to calculate inflation because the prior represents changes of consumption and cost of living better. Brent crude oil, OPEC total production are used as proxy for specific an supply shock respectively. Brent oil is preferable to other ones as it accounts for 60% of total oil consumption in the world (Maghyereh, 2004). The first nearby future price of Brent crude oil is used instead of spot price because of its advantages. Hernandez and Torero (2010) argued that future price is more accurate than spot price since the contract is standardized. Furthermore, it is used as a hedging tool by hedgers and speculators. Finally, market information is reflected better through future price formation. Reason to use OPEC total oil production is that it is the main import source of three countries. Global demand real activity is represented by dry cargo freight rate which is available at Kilian's homepage[5]. Killian (2009) explained clearly how the index is constructed. The rationale of using this index is that it measures the change of global economic activities which is reflected in the demand for shipping and transportation. Since volatility of macro variables are computed by 12th autoregressive model and number of lags in GARCH MIDAS model is 3, macro variables were taken from 01/1999 to 6/2014. All macro factors were taken log return to get month to month change. Apart from dry cargo freight rate, the other macro variables and stock price are extracted from Thompson Reuters.

5.2. Summary statistic

Appendix 2 describes summary statistic for stock returns and macroeconomic variables of all countries. It can be seen that all indices have positive mean. Among three indices, South Korea has highest mean (0.04%), the lowest belongs to China (0.016%). It means that South Korea stock market performs the best on average. Turning to standard deviation of stock returns, China stock index deviates the most from the mean (1.622) and South Korea is the most stable market (1.425). All three indices experience negative skewness indicating that they have long left tails toward negative returns.

Turning to inflation variables, average value of Japanese inflation rate is smallest (0.003%) reflecting long time of deflation in Japan. However, Japan inflation does not vary too much with standard deviation of 0.316. In the same period, the gap between lowest and highest value of inflation in China is 4.65%. It also has highest standard deviation of 0.64. South Korea government maintains inflation more stable compared to two neighbor economies. Regarding to industrial production growth, China is the unique country has positive skewness indicating its high economic growth rate during estimation period. Its highest growth is 15,12%, much higher than 6,62% and 6,89% of Japan and Korea respectively. In contrast, the

[5] Data is available at: http://www-personal.umich.edu/~lkilian/reaupdate.txt

downturn of Japan economy is reflected through high negative value of skewness (-3,02). It experienced the worst drop of industrial production growth of 17,98%. South Korea, in contrast, has highest mean and lowest standard deviation. Turning to oil price shocks, oil production growth has much lower standard deviation compare to those of specific demand and aggregate demand shocks. Therefore the demand shocks act as main drivers of real oil price shocks. Aggregate demand shock is the most volatile factor with standard deviation of 27.83. Specific demand shock also fluctuated a lot during the period from 2003-2014. Its returns vary from -81% to 50.64% and standard deviation is 17.613.

5.3. Test for stationarity

In order to assure for stationarity of series, I employed Augented Dicked-Fuller (ADF) test to test for unit root. The null hypothesis of the test is that series has unit root implying that it is non-stationary. Result of the test with test statistic is presented in Appendix 3. I performed the test both with trend and without trend. The unit root test is carried out for stock return and macroeconomic variables in GARCH MIDAS model: industrial production growth, inflation, global demand shock, supply shock and specific demand shock. The result in appendix 3 tells us that we can reject the null hypothesis in all cases. Therefore all series used in estimation process are stationary.

6. EMPIRICAL FINDINGS AND DISCUSSION

This section presents results from my regressions. These results are then analyzed and discussed further.

Table 1-5 present estimation results for inflation, industrial production growth, global demand shock, specific demand shock and supply shock respectively. The results for specification model with level of variables are shown in upper panel. Lower panel presents result with volatility specification. Estimated parameters together with statistics are shown from column 2-7. Final column displays long likelihood function (LLF) and Bayesian information criteria (BIC) underneath.

Before looking for detail how macroeconomic information contributes to long term volatility of stock market in three markets, it is noteworthy to evaluate other parameters. μ is always significant in model with data from Japan and South Korea. In contrast, α and β are always statistically significant at 1% confidence level. Sums of these two parameters are always close to and less than 1, indicating that volatility clustering is the major component of stock market volatility and macro information contributes to the long-term component variance to some extent. This finding is consistent with previous studies (Engle, Ghysels and Sohn, 2008), Engle and Rangel (2008). Turning to the effect of macro variables on stock volatility through parameter θ_l and θ_v.

Table 1: Parameter estimates of GARCH MIDAS model with inflation

Level of inflation							
	μ	α	β	m	θ_l	ω_2	LLF/BIC
China	0.0121	0.0472^{**}	0.9454^{**}	0.8848^{**}	1.4649	1^{**}	2435.16
	0.4823	6.4409	110.76	3.8980	1.2671	2.9033	4917.91
Japan	0.0640^{**}	0.1034^{**}	0.8817^{**}	0.9197^{**}	0.2819^{*}	299.99	2211.31
	2.9027	9.0243	69.974	3.4163	2.1022	0.3100	4470.29
Korea	0.0728^{**}	0.0730^{**}	0.9068^{**}	-1.1119^{*}	6.5816^{**}	1.9560^{**}	1962.47
	3.6647	8.5140	85.065	-2.5327	3.9419	4.3176	3972.68
Volatility of Inflation							
	μ	α	β	m	θ_v	ω_2	LLF/BIC
China	0.0099	0.0475^{**}	0.9463^{**}	1.0304^{**}	-0.3354	31.386	2433.25
	0.398	6.7722	119.63	3.7054	-1.5378	1.2580	4914.09
Japan	0.0633^{**}	0.1032^{**}	0.8823^{**}	0.9350^{**}	0.0972	299.99	2213.37
	2.8652	9.0204	70.694	3.3495	0.5995	0.3149	4474.41
Korea	0.0747^{**}	0.0763^{**}	0.9042^{**}	-0.6435^{*}	18.2091^{**}	3.0723^{**}	1961.79
	3.7653	8.5001	80.982	-2.2715	4.7555	4.6929	3971.32

Note: The table presents estimation results of the GARCH MIDAS model for level and volatility of inflation specifications as described in equation (9) and (12) respectively. Level and volatility of inflation are measured at monthly frequency. For both specifications, log τ_t is modeled by taking 36 lags in the MIDAS filter. Data covers periods from 01/2003-06/2014. **, * represent significance level at 1% and 5% respectively.

6.1. Inflation

For level specification, coefficients θ_l are positive in all cases, showing that an increasing in inflation rate accompanies with higher stock volatility. However only parameter estimated with data from South Korea and Japan are significant. These countries experienced less fluctuation in inflation and smaller gap during estimation period compared to China. Therefore it can be said stock market of countries with unstable inflation will be less affected by inflation. The magnitude of effect of inflation on stock market is computed through parameter θ and ω_2[6]. For South Korea, parameter estimates θ_l is 6.582 and

[6] Following Engle, Ghysels and Sohn, 2008), the effect of macro variables on stock market is: $e^{\theta * \varphi(w)} - 1$

ω_2 is 1.956. This puts the weight φ_1=0.054 on the first lag. Therefore an increasing 1% of inflation this month causes 42.68% increase in stock market volatility next month. Similarly, an increasing of 1% in inflation this month would increase stock market volatility by 32.3% next month in Japan. Turning to lower panel of table 1, only South Korean market is significant influenced by inflation uncertainty. Parameter estimate θ_v shows that stock market reacts strongly to inflation fluctuation.

Appendix 7 plots the weighting function with estimated parameter ω_2. The figure shows that the effect of inflation on stock market volatility is more persistent in South Korea than Japan. While the weight reduces gradually for South Korea, it dies quickly for Japan. Appendix 9 illustrates the comparison between total estimated variance in the GARCH MIDAS model with realized volatility[7]. The intuition behind choosing realized volatility is that it is a good measure of volatility. We can see that the total variance estimated by GARCH MIDAS model captures quite well the realized volatility for both South Korean and Japanese stock market. The comparison between long term, short term component and total variance from the GARCH MIDAS model with level of inflation is exhibited in figure 1. These figures show that long term component is above short term component all the time except some peaks. Japanese long term component is quite smooth, indicating little support for total variance. In contrast, South Korean long term variance moves together with total variance. Although it has great contribution to total variance, it is not the main driver of South Korean stock market volatility in the global crisis in 2008-2009.

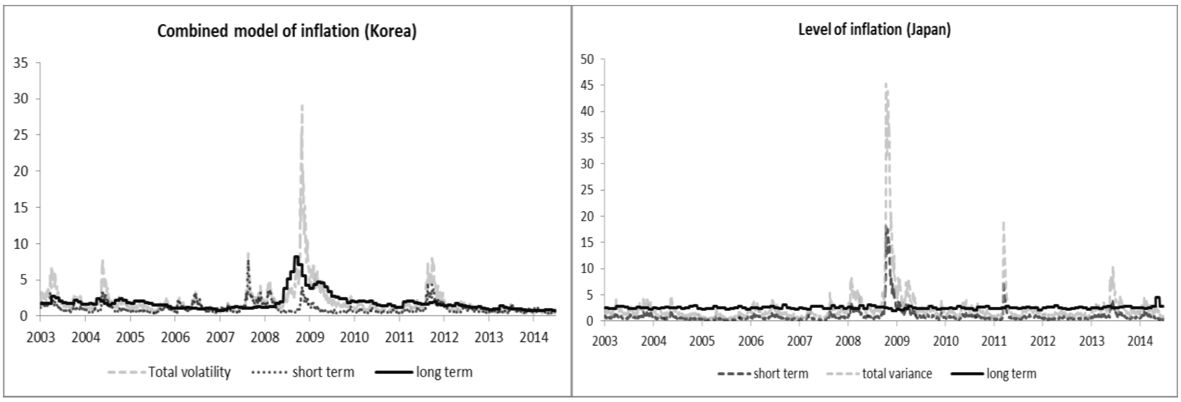


Figure 1: Plot of long-term, short-term and total variance estimated by GARCH MIDAS model. These figures illustrate the long-term, short-term components and total variance of inflation for combined specification of South Korea and level specification of Japan. Inflation level and volatility are measured at monthly frequency. For both specifications, log τ_t is modeled by taking 36 lags in the MIDAS filter. Data covers periods from 01/2003-06/2014

[7] Realized volatility $RV_t = \sum_{i=1}^{Nt} r_{i,t}^2$ where $r_{i,t}$ is the return of day i in month t

Results for specification which combines both the level and variance of inflation, described by equation (14) are reported in Appendix 5A and 5B. The results are similar to those with individual specifications. It appears just slightly different in the magnitude of effect.

Positive relationship between inflation and stock market volatility is consistent with theories and previous studies Engle, Ghysels and Sohn (2008). Although Chinese stock market is insignificant impacted by inflation, It is not surprised. In recent study, Girardin and Joyeux (2013) found a mixed effect of inflation on stock market volatility for Chinese A share and B share market. They showed that inflation level impact only A share market where domestic share is listed and is not allowed foreign investors to trade. In their paper, an increase of 1% in inflation causes a slightly effect of 0.58% volatility of A share market. In the meantime, B share market which lists foreign shares is silent to inflation. They also showed that the inflation volatility is significant in both markets. However the effect is very poor. The difference between my results and their findings may come from different data sample. I used shorter and more recent data from 2003 to 2014. This period is characterized by high inflation and output volatility due to effect of global crisis. Besides that, I used the SSE index which is the combination of both A share and B share market. Therefore speculative characteristic of B share market may affect to overall reaction of SSE index to inflation. One might expect that coefficient θ_l for Japanese data should be negative. It is due to the goal of Japanese government is to increase inflation instead of calming it down. Japanese government aims to boost aggregate demand through easing monetary policy. In other words, high inflation is expected to associate with high cash flow and low volatility. However this is not the case since Japanese monetary is ineffective. Inflation does not support for aggregate demand as expectation (Yoshino and Taghizadeh Hesary, 2014). The positive coefficient of Japan indicates that effect of inflation to discount factor is greater than effect to cash flow. As Appendix 2 shows, South Korean inflation is much higher on average compare those of China and Japan. Therefore its negative coefficient and strong reactions of stock market are not surprising.

6.2. Industrial Production growth rate

At the level, only parameter estimated with Japanese data is significant. However positive sign of θ_l is unexpected. It implies that high industrial production in Japan leads to stock market more unstable. With similar computation as previous section, an increase of 1% in industrial production growth this month would increase Japanese stock market volatility by 4.3% next month. On the other hand, volatility of industrial production does not have explanatory power except the one of China. This indicates that stock market volatility in South Korea is disconnected from real economic activity. Interestingly, parameters θ_l and θ_v estimated from combined specification are both significant for China. This implies that level of China industrial production growth influences the effect of its variance on stock market volatility. Estimated parameter ω_2 is 1.055, puts 0.03 on both the first and second lag. Therefore an increase of 1% of industrial production growth in China causes an increase of 2.75% in stock market volatility next month and the month after that.

Appendix 8 plots the long term, short term component and total variance. For Japan, the long term variance is smooth, similar to the case of inflation. In contrast, long term variance shows a close pattern with total variance in China especially after 2007. In other words stock market in China is more sensitive to information about real economic activity. Furthermore, long term component appears as the main driver of recent volatility in China. In term of persistence of effect, the influence of industrial production of China disappears after 13 months as figure appendix 7 shows. From appendix 9, we see that the total variance also follows mostly the realized variance.

Table 2: Parameter estimates of GARCH MIDAS model with industrial production growth

	Level of industrial production growth						
	μ	α	β	m	θ_l	ω_2	LLF/BIC
China	0.0107	0.0492**	0.9433**	0.9326**	0.1010	10.813	2434.46
	0.4273	6.7254	111.93	3.9290	0.8673	0.9266	4916.51
Japan	0.0633**	0.0999**	0.8870**	0.9489**	0.0430*	299.98	2210.82
	2.8647	9.0802	75.783	3.1936	2.4203	0.1845	4469.31
Korea	0.0720**	0.0762**	0.9127**	0.3730	0.4572	1.4367**	1969.99
	3.6140	8.9766	98.727	1.1705	1.3222	3.2892	3987.72
	Volatility of industrial production growth						
	μ	α	β	m	θ_v	ω_2	LLF/BIC
China	0.0132	0.0451**	0.9458**	2.1545**	-0.2517**	1.0790**	2427.9
	0.5304	6.0130	98.569	5.5484	-3.7602	10.422	4903.39
Japan	0.0627**	0.0958**	0.8948**	1.1512**	-0.0195	13.239	2208.49
	2.8453	8.9174	78.013	2.7279	-1.3619	1.3130	4464.65
Korea	0.0724**	0.0767**	0.9141**	0.6770*	-0.0027	299.27	1970.56
	3.6318	9.0634	100.49	2.2827	-0.8071	0.2192	3988.86

Note: The table presents estimation results of the GARCH MIDAS model for level and volatility of industrial production growth specifications as described in equation (9) and (12) respectively. Level and volatility of industrial production growth are measured at monthly frequency. For both specifications, log τ_t is modeled by taking 36 lags in the MIDAS filter. Data covers periods from 01/2003-06/2014. **, * represent significance level at 1% and 5% respectively.

The findings for South Korean market are consistent with study of Davis and Kutan (2003) who showed lack of significant effect of industrial production on Korean stock market. From appendix 1, we can see that industrial production in Korea slowed down after global crisis in 2009. However Korean stock market performs well. It recovers quickly and stable after 2009. While Chinese and Japanese stock price are still below the peak before the crisis, KOSPI index surpass the peak in 2007 since 2010. Hence real economic activities and Korean stock market seem to be uncorrelated. Positive impact of industrial production growth to stock volatility and reserve impact of its volatility are noteworthy. Davis and Kutan (2003), in their paper, pointed out that relationship between industrial production and stock market is mixed. While industrial production has calming effect for countries which experience good and stable economic growth, countries with high uncertainty in output are associated with high stock market volatility[8]. This is the case of Japan and China in this study. Japan has suffered economic downturn together with severe effects of global crisis in 2009 and strong earthquake in 2011. These events cause a great volatility in Japan output. This is confirmed in appendix 1. Industrial production dropped drastically in 2008 and 2011. China, on the other hand, surprises the world by impressive growth. However industrial production index growth also experiences great volatility as shown in appendix 2. Another explanation for this result is the fears of rising interest as discussed in section 2. Unexpected result of China may come from the phenomenon called reverse volatility asymmetry. Wan, Cheng and Yang (2014) documented that this phenomenon exists in Chinese stock market. Wan, Cheng and Yang figured out some special trading rules which make investors rush for a price rising. First is the price limitation, which restricts market to fluctuate in a certain range. This in turn reduces risk aversion of investors, and therefore attracts more retail investors. Chinese stock market also blocks investors from short sale activities. Consequently, it reduces arbitrage ability of investors and drives them to buy over valued stocks. Finally is the dividend policy of listed firms in Chinese stock market. Most of firms issue additional shares instead of paying cash dividend. From above reasons, Chinese investors tend to trade actively when stock price is high and inactively when price drops. It causes the positive relationship between return and volatility in China stock market.

6.3. Oil price shocks

For level specification, oil price shock stems global demand, significantly affects all three stock market indices at 5% significance level. This finding tells us that all three economies involve in global economic activities. However, direction and magnitude of impact are mixed. Chinese and South Korean stock market volatility are positively influenced by aggregate demand shocks, while an increase in aggregate demand calms down Japanese stock market volatility. An increase of 1% global demand this month causes an increase of 0.097% and 0.098% volatility of stock market next month for China and Korea respectively. At the same time, Japanese stock market volatility decreases by 0.092% due to 1% increase in global demand last month. Second moment of this shock is only significant with data from South Korea. Nevertheless, the effect is very limited. Although magnitude of effect of aggregate demand to all three markets is very poor, this factor persistently affects stock market volatility as appendix 7 shows. In contrast to South Korea and Japan which long term variance does not

[8] Davis and Kutan (2003) found positive effect of industrial production on stock market volatility with data from Belgium and Israel

contribute much to total variance, oil price shocks stems from global demand provides good contribution of secular component to Chinese stock volatility. These conclusions are interpreted from appendix 8.

Table 3: Parameter estimates of GARCH MIDAS model with aggregate demand shocks

Level of aggregate demand shocks							
	μ	α	β	m	θ_l	ω_2	LLF/BIC
China	0.0105	0.0457**	0.9386**	0.4926**	0.0221**	1.5863*	2428.53
	0.4186	6.1730	92.706	3.6044	4.3557	2.5759	4904.65
Japan	0.0648**	0.1048**	0.8769**	1.0056**	-0.0102*	3.3754	2211.66
	2.9372	8.9386	66.266	4.3069	-1.9859	1.1646	4470.99
Korea	0.0712**	0.0751**	0.9103**	0.3057	0.0159**	2.1954*	1966.22
	3.5846	8.7768	93.856	1.5170	3.0292	2.0605	3980.18
Volatility of aggregate demand shocks							
	μ	α	β	m	θ_v	ω_2	LLF/BIC
China	0.0115	0.0474**	0.9455**	1.0606**	-0.0022	1.3993	2435.64
	0.4612	6.3424	108.28	3.4776	-0.7421	1.3718	4918.87
Japan	0.0636**	0.1044**	0.8771**	0.6318*	0.0038	2.1656	2212.23
	2.8781	8.8764	65.111	2.3927	1.6658	1.2568	4472.13
Korea	0.0713**	0.0742**	0.9137**	0.9909**	-0.0067**	1.6033*	1967.45
	3.5840	8.6810	94.727	3.6785	-2.6302	2.1360	3982.64

Note: The table presents estimation results of the GARCH MIDAS model for level and volatility of aggregate demand shocks specifications as described in equation (9) and (12) respectively. Level and volatility of aggregate demand shocks are measured at monthly frequency. For both specifications, log τ_t is modeled by taking 36 lags in the MIDAS filter. Data covers periods from 01/2003-06/2014. **, * represent significance level at 1% and 5% respectively.

Similar to supply shocks, coefficients of oil price shocks stems from precautionary demand are insignificant with data from Japan and China in level specifications. South Korean stock market volatility is positively affected by specific shocks. Higher oil price induces higher volatility in stock market in South Korea. From estimated parameters, it shows that 1% increase in specific shock causes 1.2% increase in South Korean stock market next period. The coefficients θ_v of volatility specification are positive and significant with data from China and South Korea, indicating that high volatility in specific shocks is associated with high stock market volatility. Similar results are obtained with combined model of level and variance of oil price shocks.

Table 4: Parameter estimates of GARCH MIDAS model with specific demand shocks

	Level of specific demand shocks						
	μ	α	β	m	θ_l	ω_2	*LLF/BIC*
China	0.0111	0.0484**	0.9438**	0.7893**	0.1125	1.2153**	2435.04
	0.4447	6.4881	108.92	3.2962	1.3393	3.2188	4917.67
Japan	0.0653**	0.1058**	0.8724**	1.0127**	-0.1684	1.3812**	2212.27
	2.9419	8.7753	59.355	4.9332	-1.5952	3.0405	4472.21
Korea	0.0714**	0.0743**	0.9152**	0.3284	0.2390*	1.7645**	1966.51
	3.5987	9.1186	104.32	1.2290	2.5639	3.1387	3980.76
	Volatility of specific demand shocks						
	μ	α	β	m	θ_v	ω_2	LLF/BIC
China	0.0126	0.0493**	0.9405**	0.3702	0.0089*	2.4981*	2433.68
	0.5053	6.6943	105.64	1.1747	2.0187	2.0357	4914.95
Japan	0.0634**	0.1027**	0.8836**	1.0671**	-0.0022	7.8247	2213.26
	2.8712	8.9789	71.051	2.8528	-0.5683	0.6799	4474.19
Korea	0.0758**	0.0811**	0.8982**	-0.1232	0.0113**	4.1518**	1965.81
	3.8096	8.6077	71.358	-0.5469	3.9111	2.9363	3979.36

Note: The table presents estimation results of the GARCH MIDAS model for level and volatility of specific demand shocks specifications as described in equation (9) and (12) respectively. Level and volatility of specific demand shocks are measured at monthly frequency. For both specifications, log τ_t is modeled by taking 36 lags in the MIDAS filter. Data covers periods from 01/2003-06/2014. **, * represent significance level at 1% and 5% respectively.

In contrast to global demand shocks, oil supply shocks hardly affect stock market volatility. Only specification for supply volatility of South Korea is found to be significant. OPEC oil supply uncertainty significantly makes South Korean stock market more volatile. A 10% increase in volatility of oil supply shocks leads to 0.21% volatility in stock market volatility in South Korea next month.

Table 5: Parameter estimates of GARCH MIDAS model with supply shocks

Level of supply shocks							
	μ	α	β	m	θ_l	ω_2	LLF/BIC
China	0.0106	0.0477**	0.9451**	0.8772**	0.3737	1.2231	2435.56
	0.4238	6.4548	110.05	3.6522	0.8471	1.9357	4918.71
Japan	0.0633**	0.1013**	0.8848**	0.8966**	0.1609	22.5067	2211.24
	2.8739	8.9456	71.629	3.2196	1.5762	1.7135	4470.15
Korea	0.0735**	0.0745**	0.9142**	0.5375*	0.1714	29.556	1965.65
	3.6999	8.9060	98.667	2.3023	1.6300	1.2849	3979.04
Volatility of supply shocks							
	μ	α	β	m	θ_v	ω_2	LLF/BIC
China	0.0114	0.0474**	0.9458**	0.9012**	0.0328	70.351	2433.23
	0.4583	6.6369	115.78	3.6023	1.6876	0.9432	4914.05
Japan	0.0640**	0.1037**	0.8805**	0.7381*	0.0851	3.9388	2212.72
	2.8957	9.0029	69.3065	2.6008	1.4173	1.3803	4473.11
Korea	0.0740**	0.0780**	0.9052**	0.0757	0.2225**	3.6109*	1965.67
	3.7222	9.0266	66.237	0.3694	4.4362	2.0047	3979.08

Note: The table presents estimation results of the GARCH MIDAS model for level and volatility of supply shocks specifications as described in equation (9) and (12) respectively. Level and volatility of supply shocks are measured at monthly frequency. For both specifications, log τ_t is modeled by taking 36 lags in the MIDAS filter. Data covers periods from 01/2003-06/2014. **, * represent significance level at 1% and 5% respectively.

The finding of aggregate demand shocks with data from China is inconsistent and differs from that of Fang and You (2014), who reported insignificant results. The difference may come from the different data sample in two studies. My study is carried out for recent period which reflects better the role of China in global economy. The difference in responding of three markets to the same shocks, aggregate demand shocks, is noteworthy. Positive relationship between global demand shock and stock market volatility in China can be partly explained by reverse asymmetry volatility as the case of industrial production. Although there has never any research on this phenomenon in South Korea, this seems that it also exists in South Korean market. South Korean market shares some similar characteristics with Chinese market. Firstly, retail investors with less knowledge about trading also dominated the market (Nartea, Wu, Liu, 2014). According to Korean stock exchange fact book, the number of institutions and their total value traded are less than 20% in comparison with individual investors are. Secondly, investors are also restricted from short sales activities. Korean stock exchange sets the limit of 15% to avoid stock price drop or increase over 15% compare to closing price of last trading day[9]. From these arguments, reverse asymmetry volatility phenomenon is likely exist in South Korean stock market. In addition, Kwon and Shin (1999) confirmed in their paper that South Korean investors have different point of view about stock prices movement compare to those in Japanese and US markets. From the discussion in section 2, it can be also argued that negative effect of oil prices shocks stems from global demands outweighs positive effect.

Another remarkable result is that South Korean stock market volatility is linked to both supply and specific demand shock while Japanese market is silent. This may be due to the difference in energy policies of two countries. First, Japan develops technology to increase oil efficient consumption and lower dependence on oil import. In comparison with other developed countries, Japan has the lowest energy intensity. As a result, proportion of oil in total energy consumption in Japan has declined significantly from 80% in 1970s to 44% in 2013. In addition, Japan has also maintained a good strategic stock of about 100 days consumption and leased some crude oil storages in United Arab Emirates and Saudi Arabia which assures for advantages to buy oil in the case of disruption in oil supply[10]. Therefore Japan reduces risks exposed to oil market. In the meantime, petroleum is still the main energy of South Korea. It accounts for 41% consumption of total energy in 2012. As a consequence, there is close linkage between oil price shocks and South Korean stock market as the findings indicated.

6.4. Measuring contributions of macroeconomic sources to stock market volatility

In order to measure contribution of macroeconomic variables to total expected volatility, I follow Engle, Ghysels and Sohn (2008) to compute the ratio: Var $(\log(\tau_t))/\mathrm{Var}(\log(g_{it} * \tau_t))$ for each model specifications. The results are reported in appendix 6. Among three countries, expected volatility of China is contributed the most by macro variable. In the model with level of aggregate demand the long term component contributes 48% to stock market volatility. Besides that, volatility of industrial production is also a huge resource of stock market volatility in China. Apart from industrial production, the other variables have moderate impact on expected volatility of South Korea. It ranges from 17 to 25% for level and volatility specifications. It is not surprised to observe the contribution of 44.64% of long term

[9] KRX Fact Book, 2013 [online] Available at: < http://eng.krx.co.kr/coreboard/BHPENG08004/view.jspx?bbsSeq=19801&secretYn=N> [Accessed 20 April 2015]

[10] EIA, 2015. Japan full report. [online] Available at < http://www.eia.gov/countries/cab.cfm?fips=JA> [Accessed 20 April 2015]

component to total variance in South Korea with the combined model of inflation. In contrast to South Korea and China, Japanese stock market is less driven by macro variables. The biggest contribution comes from the model estimated with volatility of industrial production, which accounts for 14% of total stock market volatility. These results are consistent with what is displayed in appendix 8 and analysis in the empirical results section. The smoother long term variance, the less contribution it does for total variance. This is decided by two factors: the value of θ and the beta weight parameter ω_2. Low value of parameter theta is accompanied by smooth long term variance. High value of parameter ω_2 also lessens the contribution of long term variance as the effect of economic factor dies out quickly.

6.5. Different determinants of markets.

A nice feature of GARCH MIDAS model is that the set of parameter is fixed. Therefore we can make a comparison to see which model achieve the best fit by looking at the log likelihood values or BIC. Overall, different markets have different determinants. For China, the best fit model is obtained by including the information from industrial production. The models incorporating aggregate demand shocks also yield good fit. In opposite, specific demand and supply shocks models show the worst fit. For Japan, the industrial production growth outperforms other variables. In the meantime, the oil supply shocks and specific demand shocks perform the worst. For Korea, both inflation level and uncertainty achieve the best fit. These results confirm that factors which have greater impact on stock market volatility would yield better fit.

7. CONCLUSION

This section summarizes key findings of the paper. Limitations as well as suggestions for further studies are also presented.

My thesis aims to investigate the impact of macroeconomic variables to stock market volatility. The motivation for this thesis arises from the importance of the stock market volatility to the decision of policy makers and market participants. Due to growing role of Asian economies in recent years, I focus on three leading markets China, South Korea and Japan. The study covers the period from 2003 to 2014 which is characterized by economic difficulties in Japan, a good economic growth of China and South Korea and severe effects of global crisis. I used GARCH MIDAS model for my study. This model has some advantages compared to conventional volatility model. First, it allows to estimate long term and short term component variance separately. Second, it allows to link macroeconomic which is measure at lower frequency directly into models.

The main findings can be summarized as follow. Firstly, the responses of stock market are different among three countries. While Chinese and South Korean stock markets are affected by either inflation or industrial production, Japanese stock market reacts to both of them. The magnitude of effect is also different. Japanese reacts to macro information at limited degree. In the meantime, information about inflation and industrial production has strong power in explaining stock market volatility in China and South Korea. Perception of investors and characteristics of market are reflected by reactions of three markets to the same oil price shocks. While Japan market volatility is calmed down by an increase in the oil price shocks stem from aggregate demand, China and South Korea stock volatility are positively correlated with this factor. Japanese market is known as the developed and efficient market. In contrast, Korean and Chinese stock market are immature. Reaction of stock market to oil price shocks also sheds light on the energy dependence of these countries. Japan reacts to only to aggregate demand shocks thanks to its oil strategies, South Korea depends on both specific demand and oil supply shocks due to great dependence on oil import source.

There are some limitations in my thesis. First, I do not perform the test for structural break in volatility model. Existing literatures have confirmed the existence of structural break in volatility (Engle, Ghysels and Sohn, 2008). By studying sub samples, we can know different effects of macroeconomic variables on stock market volatility in different time and economic situation. In addition, forecasting power is left for future studies. For further studies, I would estimate various kinds of volatility models such as GARCH, Spline GARCH in order to make a comparison among them. Hence we can know which kind of model yields the best result and which model has more power in predicting stock market volatility. Another suggestion is to incorporate more economic variables and combine them in one model to see both the effects of individual factor and detect correlation or overlap between variables.

REFERENCES

Abhyankar, A., Xu, B., & Wang, J. (2013). Oil price shocks and the stock market: evidence from Japan. *Energy Journal, 34*(2), 199-222.

Asgharian, H., Hou, A. J., & Javed, F. (2013). The Importance of the Macroeconomic Variables in Forecasting Stock Return Variance: A GARCH-MIDAS Approach. *Journal of Forecasting, 32*(7), 600-612.

Attari, M. I. J., Safdar, L., & Student, M. (2013). The Relationship between Macroeconomic Volatility and the Stock Market Volatility: Empirical Evidence from Pakistan. *Pakistan Journal of Commerce and Social Sciences, 7*(2), 309-320.

Black, F. (1976). Studies of stock price volatility changes. *Proceedings of the American Statistical Association (1976)*, pp. 177–181 Business and Economics Statistics Section

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics, 31*(3), 307-327.

Chen, N.-F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of business*, 383-403.

Chen, Q. a., Fang, P., & Zhang, Y. (2012). Changes in Macroeconomic Policies and Volatility of Chinese Stock Market. *Journal of Software, 7*(10), 2229-2235.

Chinzara, Z. (2011). MACROECONOMIC UNCERTAINTY AND CONDITIONAL STOCK MARKET VOLATILITY IN SOUTH AFRICA*. *South African Journal of Economics, 79*(1), 27-49.

Chris, B. (2008). Introductory econometrics for finance. *Cambridge Books*.

Christie, Andrew A. "The stochastic behavior of common stock variances: Value, leverage and interest rate effects." *Journal of financial Economics* 10.4 (1982): 407-432.

Cong, R.-G., Wei, Y.-M., Jiao, J.-L., & Fan, Y. (2008). Relationships between oil price shocks and stock market: An empirical analysis from China. *Energy Policy, 36*(9), 3544-3553.

Davis, N., & Kutan, A. M. (2003). Inflation and output as predictors of stock returns and volatility: international evidence. *Applied financial economics, 13*(9), 693-700.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987-1007.

Engle, R. F., Ghysels, E., & Sohn, B. (2008). *On the economic sources of stock market volatility.* Paper presented at the AFA 2008 New Orleans Meetings Paper.

Engle, R. F., & Rangel, J. G. (2008). The spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *Review of Financial Studies, 21*(3), 1187-1222.

Errunza, V., & Hogan, K. (1998). Macroeconomic determinants of European stock market volatility. *European Financial Management, 4*(3), 361-377.

Fang, C.-R., & You, S.-Y. (2014). The impact of oil price shocks on the large emerging countries' stock prices: Evidence from China, India and Russia. *International Review of Economics & Finance, 29*, 330-338.

Fischer, S., & Modigliani, F. (1978). Towards an understanding of the real effects and costs of inflation. *Weltwirtschaftliches Archiv, 114*(4), 810-833.

Fisher, I. (1930). The theory of interest. *New York*, *43*.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2005). There is a risk-return trade-off after all. *Journal of Financial Economics, 76*(3), 509-548.

Girardin, E., & Joyeux, R. (2013). Macro fundamentals as a source of stock market volatility in China: A GARCH-MIDAS approach. *Economic Modelling, 34*, 59-68.

Goffe, W. L., Ferrier, G. D., & Rogers, J. (1994). Global optimization of statistical functions with simulated annealing. *Journal of econometrics, 60*(1), 65-99.

Hasanov, M., & Omay, T. (2011). The relationship between inflation, output growth, and their uncertainties: Evidence from selected CEE countries. *Emerging Markets Finance and Trade, 47*(sup3), 5-20.

Hernandez, M., & Torero, M. (2010). Examining the dynamic relationship between spot and future prices of agricultural commodities: International Food Policy Research Institute (IFPRI).

Huberman, G. (2005). *Arbitrage pricing theory* (No. 216). Staff Report, Federal Reserve Bank of New York.

Humpe, A., & Macmillan, P. (2009). Can macroeconomic variables explain long-term stock market movements? A comparison of the US and Japan. *Applied financial economics, 19*(2), 111-119.

Judson, R., & Orphanides, A. (1999). Inflation, volatility and growth. *International Finance, 2*(1), 117-138.

Kearney, C., & Daly, K. (1998). The causes of stock market volatility in Australia. *Applied financial economics, 8*(6), 597-605.

Kilian, L. (2009). Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market. *American Economic Review*, 99(3), 1053-69.

Kilian, L., & Park, C. (2009). The impact of oil price shocks on the us stock market*. *International Economic Review, 50*(4), 1267-1287.

Kwon, C. S., & Shin, T. S. (1999). Cointegration and causality between macroeconomic variables and stock market returns. *Global Finance Journal, 10*(1), 71-81.

Lehmann, Bruce N., and David M. Modest. "The empirical foundations of the arbitrage pricing theory." *Journal of Financial Economics* 21.2 (1988): 213-254.

Liljeblom, E., & Stenius, M. (1997). Macroeconomic volatility and stock market volatility: empirical evidence on Finnish data. *Applied financial economics, 7*(4), 419-426.

Maghyereh, A. (2004). Oil price shocks and emerging stock markets: A generalized VAR approach. *International Journal of Applied Econometrics and Quantitative Studies, 1*(2), 27-40.

Magrini, E., & Donmez, A. (2013). Agricultural Commodity Price Volatility and Its Macroeconomic Determinants: A GARCH-MIDAS Approach: Institute for Prospective and Technological Studies, Joint Research Centre.

Masih, R., Peters, S., & De Mello, L. (2011). Oil price volatility and stock price fluctuations in an emerging market: evidence from South Korea. *Energy Economics, 33*(5), 975-986.

Mukherjee, T. K., & Naka, A. (1995). Dynamic relations between macroeconomic variables and the Japanese stock market: an application of a vector error correction model. *Journal of Financial Research, 18*(2), 223-237.

Nartea, G. V., Wu, J., & Liu, H. T. (2014). Extreme returns in emerging stock markets: evidence of a MAX effect in South Korea. *Applied financial economics, 24*(6), 425-435.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, 347-370.

Nieto, B., Novales Cinca, A., & Rubio, G. (2014). Macroeconomic and Financial Determinants of the Volatility of Corporate Bond Returns. *Available at SSRN 2442254*.

Olweny, T., & Omondi, K. (2011). The effect of macro-economic factors on stock return volatility in the Nairobi stock exchange, Kenya. *Economics and Finance Review, 1*(10), 34-48.

Papapetrou, E. (2001). Oil price shocks, stock market, economic activity and employment in Greece. *Energy Economics, 23*(5), 511-532.

Park, J., & Ratti, R. A. (2008). Oil price shocks and stock markets in the US and 13 European countries. *Energy Economics, 30*(5), 2587-2608.

Ratti, R. A., & Hasan, M. Z. (2013). Oil price shocks and volatility in Australian stock returns. *Economic Record, 89*(S1), 67-83.

Reyes, Mario G. "Asymmetric volatility spillover in the Tokyo stock exchange." *Journal of Economics and Finance* 25.2 (2001): 206-213.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of economic theory, 13*(3), 341-360.

Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics, 21*(5), 449-469.

Schwert, G. W. (1989). Why does stock market volatility change over time? *The journal of finance, 44*(5), 1115-1153.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk*. *The journal of finance, 19*(3), 425-442.

Wan, D., Cheng, K., & Yang, X. (2014). The reverse volatility asymmetry in Chinese financial market. *Applied financial economics, 24*(24), 1555-1575.

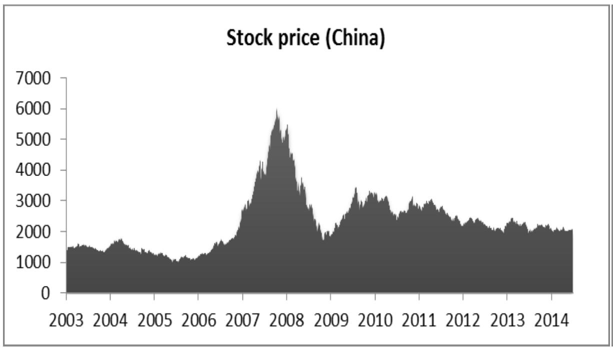
Wang, F., & Ghysels, E. (2008). Statistical Inference for Volatility Component Models. *Available at SSRN 1273381*.

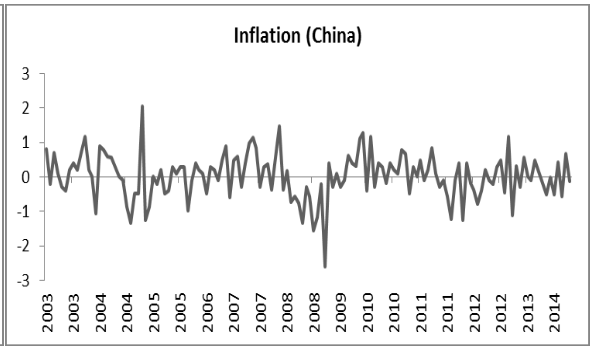
Yoshino, N., & Taghizadeh Hesary, F. (2014). Effectiveness of the Easing of Monetary Policy in the Japanese Economy, Incorporating Energy Prices.

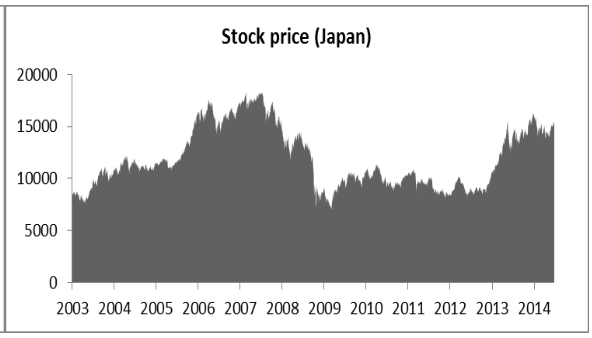
Zakaria, Z., & Shamsuddin, S. (2012). Empirical evidence on the relationship between stock market volatility and macroeconomics volatility in Malaysia. *Journal of Business Studies Quarterly, 4*(2), 61-71.

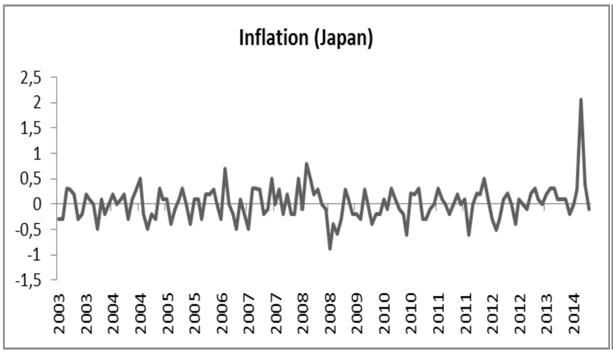
APPENDICES

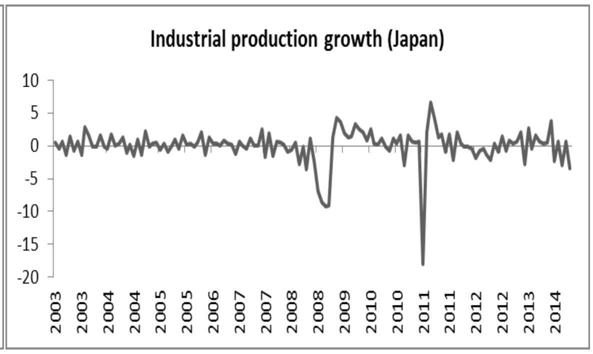
Appendix 1: Plot of stock prices, inflation rate, industrial production growth and three components of real oil price shocks.











These figures illustrate daily stock prices of three markets and monthly macroeconomic variables from 01/2003-06/2014.

Appendix 2: Summary statistic

	Mean	Median	Std Dev	Kurtosis	Skewness	Range	Min	Max
				Stock return				
China	0.016	0.031	1.622	3.689	-0.242	18.291	-9.2256	9.034
Japan	0.020	0.057	1.549	7.816	-0.573	25.346	-12.111	13.235
South Korea	0.041	0.091	1.425	6.172	-0.492	22.456	-11.172	11.284
				Inflation				
China	0.019	0.049	0.643	1.393	-0.345	4.648	-2.608	2.04
Japan	0.003	0	0.316	9.409	1.419	2.936	-0.878	2.058
South Korea	0.239	0.202	0.376	-0.141	0.115	1.895	-0.605	1.29
				Industrial production				
China	0.002	-0.0858	3.018	10.509	0.351	29.516	-14.394	15.121
Japan	-0.035	0.303	2.459	18.255	-3.019	24.604	-17.979	6.625
South Korea	0.442	0.447	2.304	6.357	-1.222	18.108	-11.218	6.890
				Oil price shocks				
Global demand	8.798	9.824	27.827	-0.956	-0.097	109.116	-48.671	60.444
Specific demand	1.715	2.965	17.613	2.629	-0.868	131.71	-81.073	50.637
Supply	0.081	0.137	1.784	3.743	-0.151	12.573	-6.308	6.265

This table shows summary statistic of stock returns of three markets and macroeconomic variables. Data cover period from 01/2003-06/2014.

Appendix 3: Unit root test

Panel A: Macroeconomic variables and stock return

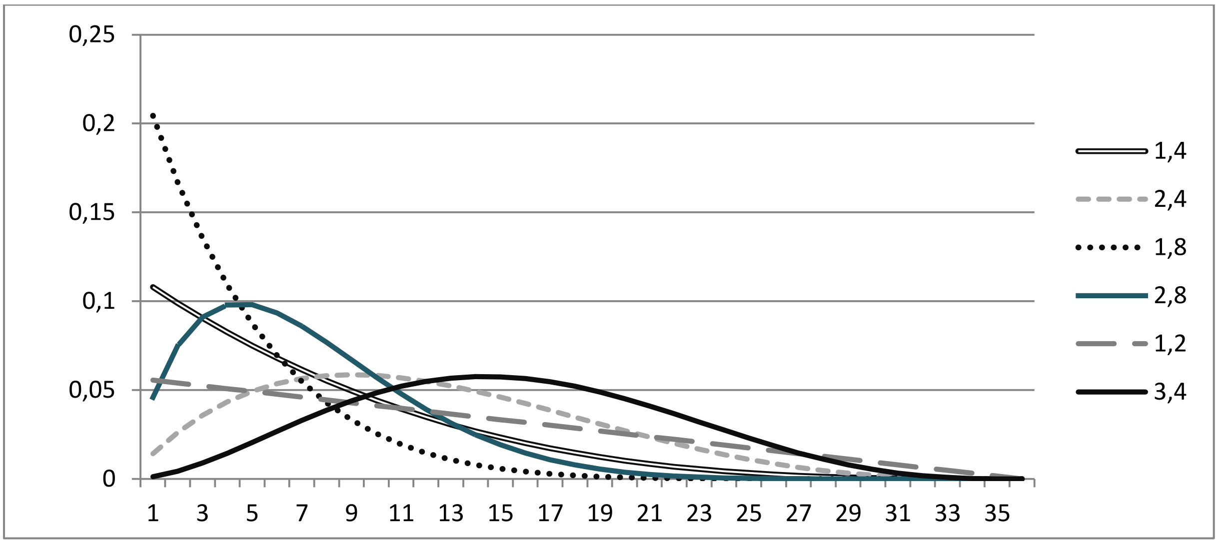
Variables	China		Japan		South Korea	
	Without trend	With trend	Without trend	With trend	Without trend	With trend
Stock return	-52.47***	-52.48***	-54.98***	-54.97***	-52.14***	-52.15***
Inflation	-5.37***	-5.35***	-9.33***	-9.38***	-9.80***	-9.87***
IP	-10.31***	-10.28***	-9.29***	-9.26***	-10.93***	-10.94***

Panel B: Oil price shocks

	Without trend	With trend
Global demand shocks	-2.58*	-3.99**
Specific demand shocks	-8.75***	-8.74***
Supply shocks	-13.82***	-13.9***

Note: These tables present results of ADF unit root test for stock returns and macro variables. Data cover period from 01/2003-06/2014. ***,**, * indicate significance level at 1%, 5% and 10% respectively

Appendix 4: Plot of beta weight functions corresponding to different values of ω_1 *and* ω_2



Appendix 5A: Parameter estimates of GARCH MIDAS model with combination of level and volatility of inflation and industrial production growth.

Inflation

	μ	α	β	m	θ_l	θ_v	ω_2	LLF/BIC
China	0.010	0.048**	0.946**	1.032**	-0.012	-0.338	31.29	2433.24
	0.399	6.772	119.6	3.710	-0.114	-1.536	1.250	4922.00
Japan	0.064**	0.103**	0.881**	0.922**	0.345*	-0.143	299.9	2211.05
	2.903	8.999	69.52	3.469	2.153	-0.721	0.242	4477.71
Korea	0.074**	0.0732**	0.904**	-1.158**	3.287*	13.36**	2.887**	1958.02
	3.756	8.251	78.55	-3.433	2.472	-3.559	5.099	3971.74

Industrial production growth

	μ	α	β	m	θ_l	θ_v	ω_2	LLF/BIC
China	0.116	0.045**	0.945**	2.168**	0.904*	-0.263**	1.055**	2424.64
	0.467	6.121	119.6	6.261	2.542	-4.416	11.71	4904.80
Japan	0.063**	0.096**	0.895**	1.127**	0.022	-0.018	13.546	2208.46
	2.844	8.908	77.55	2.657	0.266	-1.161	1.276	4472.53
Korea	0.072**	0.077**	0.912**	0.229	0.415	0.030	1.352**	1969.69
	3.625	8.933	97.09	0.655	1.175	0.780	2.818	3995.08

Note: The tables present estimation results of the GARCH MIDAS model for combined specifications of inflation and industrial production growth as described in equation (14). Level and volatility of macro variables measured at monthly frequency. For both specifications, log τ_t is modeled by taking 36 lags in the MIDAS filter. Data covers periods from 01/2003-06/2014. **, * represent significance level at 1% and 5% respectively.

Appendix 5B: Parameter estimates of GARCH MIDAS model with combination of level and volatility of oil price shocks.

Aggregate demand shocks

	μ	α	β	m	θ_l	θ_v	ω_2	LLF/BIC
China	0.010	0.046**	0.937**	0.323	0.023**	0.002	2.619*	2428.16
	0.408	6.253	91.07	1.677	4.653	1.290	2.082	4911.84
Japan	0.065**	0.105**	0.875**	0.833**	-0.008	0.002	2.574	2211.43
	2.928	8.908	64.29	2.616	-1.306	0.707	1.461	4478.47
Korea	0.071**	0.074**	0.911**	0.526	0.013	-0.003	1.668*	1965.87
	3.577	8.668	92.94	1.598	1.857	-0.854	2.034	3987.44

Specific demand shocks

	μ	α	β	m	θ_l	θ_v	ω_2	LLF/BIC
China	0.013	0.049**	0.940**	0.153	0.076	0.011*	2.278	2432.78
	0.528	6.588	103.2	0.377	0.982	2.063	1.439	4921.08
Japan	0.065**	0.106**	0.872**	1.095**	-0.175	-0.001	1.355**	2212.24
	2.946	8.769	59.19	2.662	-1.774	-0.232	3.036	4480.09
Korea	0.074**	0.076**	0.905**	-0.331	0.122	0.013**	3.599**	1961.91
	3.715	8.636	80.59	-1.177	1.943	3.497	2.440	3979.52

Supply shocks

	μ	α	β	m	θ_l	θ_v	ω_2	LLF/BIC
China	0.011	0.047**	0.946**	0.901**	-0.002	0.033	70.79	2433.23
	0.451	6.615	115.5	3.613	-0.061	1.707	0.974	4921.98
Japan	0.064**	0.102**	0.884**	0.871**	0.143	0.021	23.94	2211.03
	2.903	8.925	71.32	3.056	1.403	0.673	1.556	4477.67
Korea	0.073**	0.076**	0.908**	0.139	0.364	0.173*	5.185	1964.36
	3.673	8.843	89.38	0.619	1.736	2.564	1.802	3984.42

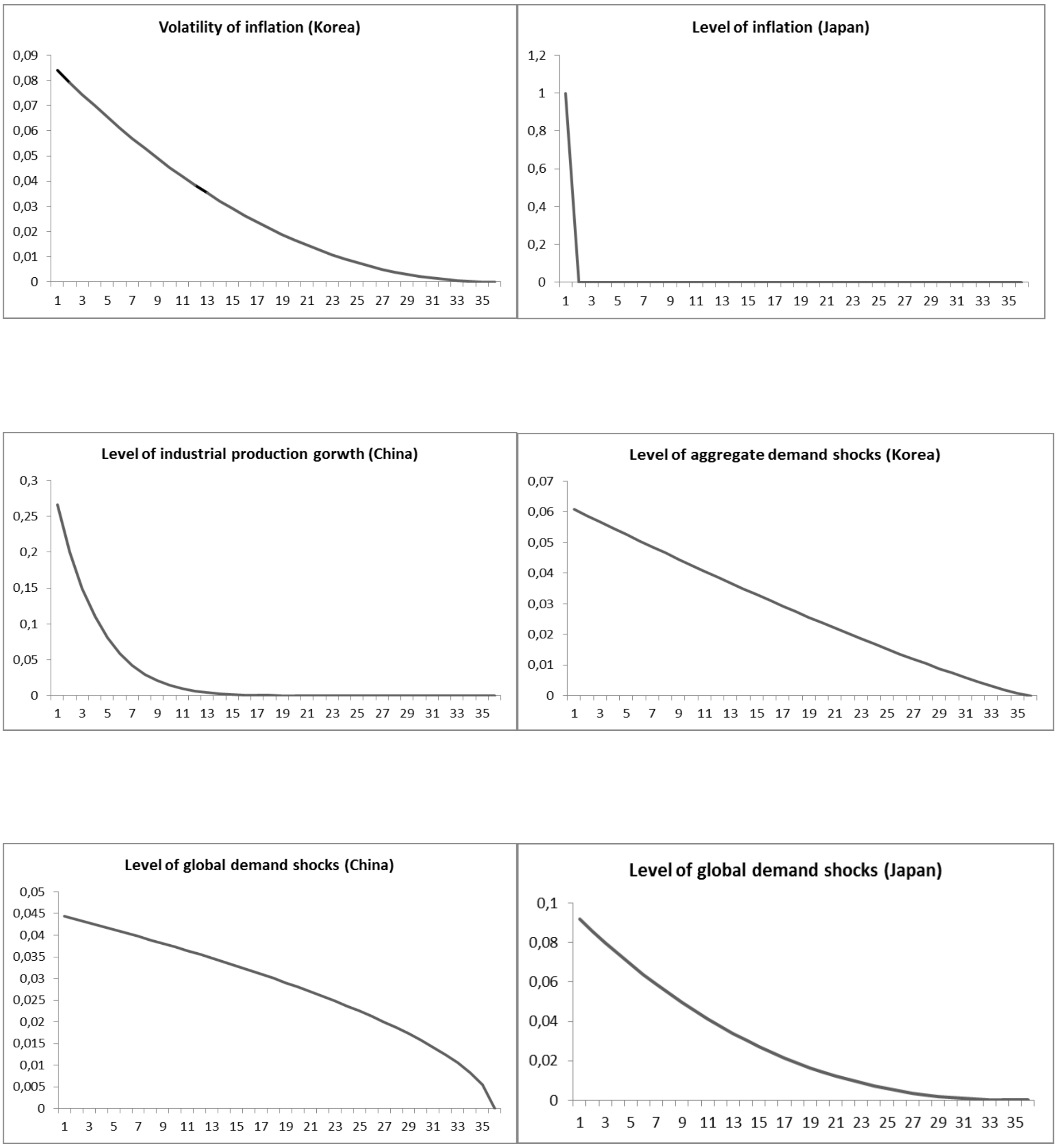
Note: The tables present estimation results of the GARCH MIDAS model for combined specifications of oil price shocks as described in equation (14). Level and volatility of oil price shocks are measured at monthly frequency. For both specifications, log τ_t is modeled by taking 36 lags in the MIDAS filter. Data covers periods from 01/2003-06/2014. **, * represent significance level at 1% and 5% respectively.

Appendix 6: Variance ratios

	Inflation	Industrial	Aggregate	Specific	Supply
			Level		
China	2.41	1.1	48.11	3.68	1.89
Japan	1.98	2.68	11.5	7.85	4.85
South Korea	25.67	2.63	20.75	17.23	5.83
			Volatility		
China	2.78	54.78	2.23	11.93	3.12
Japan	0.1	14.72	7.36	1.59	4.74
South Korea	39.25	0.23	16.61	21.44	26.41
			Combine		
China	2.77	47.32	53.42	14.24	3.13
Japan	2.36	13.92	11.3	7.5	4.36
South Korea	44.64	3.35	17.59	20.94	24.98

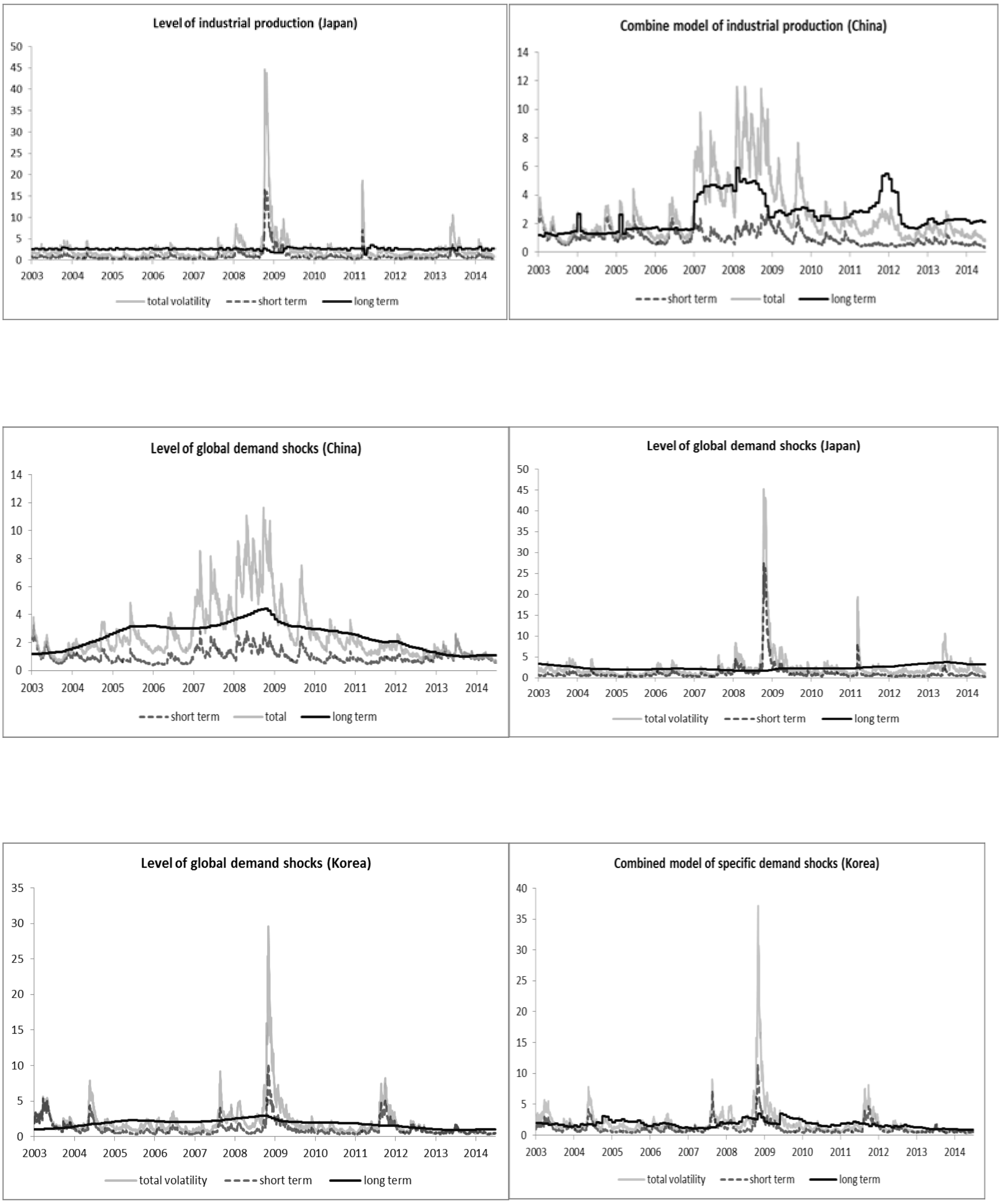
This table shows the variance ratios computed by formula: Var ($\log(\tau_t)$)/Var($\log(g_{it} * \tau_t)$). This ratio is computed for all specifications and variables.

Appendix 7: Beta weights function of selected models



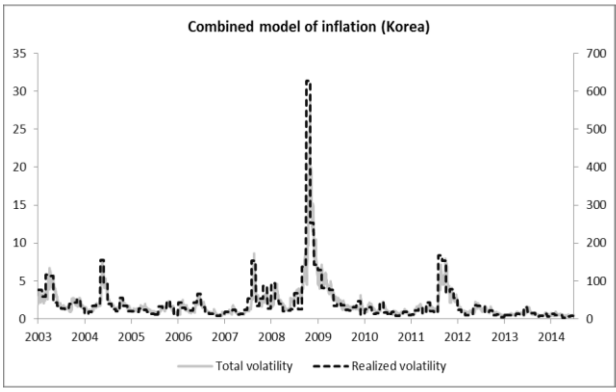
These figures illustrate optimal beta weights function of GARCH MIDAS model with monthly data of selected macro variables and 36 lags in the MIDAS filter. The horizontal axis shows the time in months, while the vertical axis is the weights.

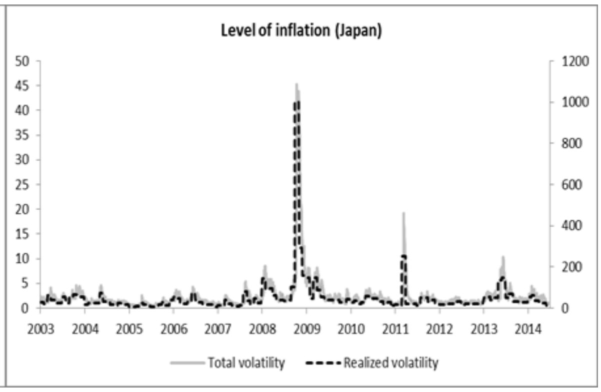
Appendix 8: Plot of conditional volatility, its short term and long term components

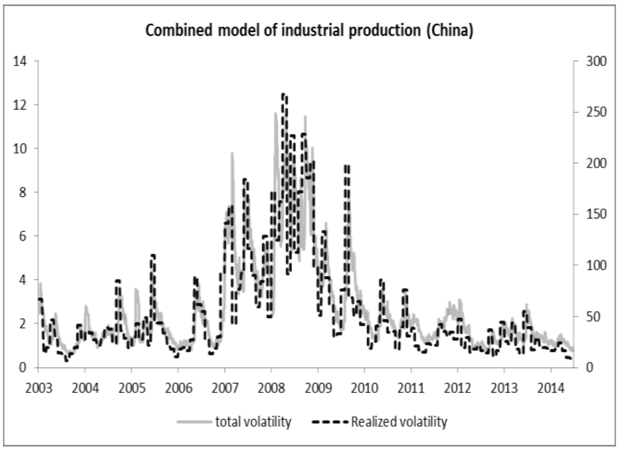


These figures illustrate the long-term, short-term components and total variance of selected macro variables and specifications estimated by GARCH MIDAS model. Macro variables are measured at monthly frequency. For both specifications, log τ_t is modeled by taking 36 lags in the MIDAS filter. Data covers periods from 01/2003-06/2014.

Appendix 9: Comparison of total variance estimated by GARCH MIDAS model and realized variance







These figures illustrate total variance estimated by GARCH MIDAS model and realized volatility of selected macro variables and specifications. Macro variables are measured at monthly frequency. For both specifications, log τ_t is modeled by taking 36 lags in the MIDAS filter. Data covers periods from 01/2003-06/2014.