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Volatility of steel prices between the Chinese and US stock markets

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Abstract

This paper examines return and volatility spillover across the Chinese and US steel and stock markets. Weekly return data of the SSE composite index, S&P 500 index and indices of the steel prices in China and the US are used. Firstly, a VAR model is used to estimate return spillovers. The resulting residuals are used in a BEKK-GARCH model to estimate volatility spillovers. The main findings of this study show that return spillover effects are almost non-existent between all markets tested except for positive return spillover effects from both steel markets own shocks. Bilateral volatility spillover was found between all markets tested except for a spillover from the Chinese stock market to the US steel market. Apart from this exception, the results indicate that the stock and steel markets nearly all influence each other's volatility.

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1. Introduction

This Thesis researches return and volatility spillover between steel prices and the Chinese and US stock market. In terms of commodities, the steel market is runner up for most valuable market after the oil market. Despite this fact, steel products are relatively new on the futures market. Steel futures started trading from 2008 and onwards, in comparison to non-ferrous metals futures which started trading in the 1920's. Futures of steel products were added on the London Metal Exchange and the New York Metal exchange in 2008. The Shanghai Metal Exchange followed in 2009. The reason for adding steel products on these exchanges was that the steel market was becoming more volatile. This makes the steel futures market a relatively immature market in comparison to other metals which were already long established on the metal futures exchanges (Arik & Mutlu, 2014).

China is the biggest consumer and producer of steel in the world. The US follows China as the runner up biggest steel consumer and producer in the world (Worldsteel, 2020). The Chinese economy slowed down in 2015 and had the lowest growth percentage in 25 years. As a result, the demand for steel and other metal products decreased. The low Chinese demand led to the dumping of the Chinese steel product surpluses on the US steel market. Therefore, international steel prices lowered. Popescu, Nica and Ștefănescu-Mihăilă (2016) researched the effects of the steel surplus on the American steel market and found that the steel industry in the US was troubled because of the excess production capacity. It becomes clear that China has a big impact on the steel prices around the world. Moreover, this could also lead to effects on volatility. Given the former and the relative immaturity of the steel futures market the following research question is formulated:

How do the returns and volatility between the steel prices and the stock markets of China and the US interact?

To answer the research question, this thesis will look at the return and volatility spillover of the steel prices in both China and the US on the stock markets of China and the US. The Shanghai Stock Exchange composite index and the S&P 500 index is used to represent the stock markets. A full VAR-BEKK-GARCH model will be used to model the returns and the volatilities of the steel prices and the stock markets as well as the interlinkages and effects of one on another. Numerous researches about volatility spillovers have been done on other commodities like oil and gold. Papers about the volatility spillovers in other metal markets, like the non-ferrous metal markets also exist. The aim of this study is to fill the gap of research done on the effects of volatility on steel markets. The results from the multivariate VAR-BEKK model show that volatility spillover exists across all observed markets except for a spillover from the Chinese stock market to the US steel market. The findings in this study could be useful for portfolio managers as it shows the possibilities of hedging portfolios invested in the steel industry.

The remainder of the thesis is structured as follows. Section 2 describes the literature review where previous research on this subject and the theories that this study uses are reviewed. Section 3 discusses the data and the empirical methods used to answer the research question. The methods used to assess the level of spillover will be determined here. Section 4 discusses the results of the methodology, the empirical results. The last section, section 5 concludes the thesis and gives recommendations for future research.

2. Literature review

This thesis focusses on the research of volatility spillover between steel markets and stock markets. Many research has been conducted on spillover effects of commodities on stock markets and vice versa. The prices of many commodities have been empirically researched for certain effects on a variety of different stock markets around the world. Crude oil and precious metals are popular subjects when researching volatility spillover on stock markets. Many research has been done on this matter. In a study by Yu, Za and Stafylas (2019) dependences and volatility spillover effects between the oil and stock markets are researched. A VAR-BEKK-GARCH is used to model the volatility spillover. They observed the oil price and the stock markets of China and the US in the period from 1991 until 2016. One of their main findings is that the Bilateral volatility spillovers between the US and China where low in the earlier period but increased in the final periods.

Kang, McIver and Yoon (2017) researched the dynamic spillover effects among precious metals commodity futures markets and crude oil. In the period from 2002 to 2016 they observed that volatility and return spillover effects increase in times of economic distress. A DECO-GARCH was used, the correlations across all pairs of assets are equal, however the common equicorrelation is time varying in this model. In this study, the BEKK-GARCH variant is used to keep correlations of the returns and volatility of the stock markets and steel prices varying. Research on volatility spillover in the non-ferrous metal futures market has been conducted as well. However, this is different from what is researched in this thesis, which researches volatility spillover of the ferrous metal steel. Todorova and Worthington (2014) analysed the non-ferrous metals in a study about the volatility transmission of five base metals with a multivariate HAR model. They were able to split the short- mid- and long-term spillover effects. Their main finding is that in the long run the largest volatility spillover effects take place between the metals. The outcome of this study suggests that this is because of the complementary and substitutionary nature between these metals.

The two studies mentioned above do not focus on the metal steel specifically. Although, research on the volatility spillover in spot and futures markets of steel related commodities in China is present in a recent paper by Kim and Lim (2019). Who studied the spillover between different futures of specific steel products in China. They found that all steel commodities in China have spillover effects between the spot and futures market except for the rebar market. The rebar is a specific steel product. On the rebar market spillover effects only existed from the spot to the futures market. They did not research the volatility effects of steel on the stock markets of countries.

In general, the studies discussed above include the spillover effects between different commodities and metals. However, they do not include the spillover effects between commodities and stock markets. Vardar, Coşkun and Yelkenci (2018) did research the effects of shock transmission and volatility spillovers in stock and commodity markets. They compared the spillover effects of oil, gas, platinum, silver and gold in a selection of advanced and emerging countries stock markets. The time period observed was from 2005 to 2016 so the pre- and after financial crisis time period was observed. The possible changes in spillover effects between these sub-periods could be compared. This study used a VAR-BEKK-GARCH model. This model is used to account for the own- and cross- volatility spillover effects between the stock markets. They found that the shock and volatility spillover effects where greater in the period after the financial crisis. Also, the interaction effects between the emerging and advanced countries increased after the crisis.

Mensi, Al-Yahyaee and Khang (2018) studied the volatility spillovers in stock markets and precious metal markets, as well as the portfolio implications. In this paper, a DECO-FIGARCH model was used to model the spillover effects by measuring the equicorrelation between stock markets and the precious metal markets. They found that the stock indices have a greater impact on the precious metal prices. Therefore, the volatility spillover of the precious metal prices on the stock markets was noticeably low. It will be interesting to see if the same results come forward in this study looking at the steel prices.

Arouri, Lahiani and Nguyen (2015) did study the spillover effects between commodities and stock markets. They researched linkages between world gold prices and stock returns in China. A VAR-GARCH model was used, five different multivariate GARCH models were tested. However, the best results were given by a VAR-GARCH model. This paper concluded that return and volatility spillover between gold prices and the Chinese stock market were minimal, so gold acted as a hedge for stocks in times of financial crisis. A similar connection between steel and the stock markets is not expected although Kang et al. (2017) proved that the spillover effects of volatility between both crude oil and precious metals increase during a financial crisis. Studies on steel prices specifically have not been discussed yet. No specific research on the volatility spillover on the Chinese and US stock markets exists.

In a study by Husain, Tiwari and Sohag (2019) the connectedness among crude oil, stock indices and metal prices in the USA is researched. The method they used to measure the volatility spillover was a generalized VAR forecast error variance decomposition approach. They found that steel markets are a receiver of volatility from the American stock markets and the precious metals markets. The volatility spillovers have fluctuated a lot according to Husain et al. due to the financial crisis in 2008-2009 and the European sovereign debt crisis during 2010-2012.

The final study that will be discussed is from Gutierrez and Vianna (2018). The study focusses on the price effects of steel commodities on worldwide stock market returns. The stock markets of a variety of emerging and developed countries including the stock markets of China and the US were examined. Weekly frequent data for the commodity prices and stock markets in the period from 2002 to 2015 was used. A VAR-GARCH model is used to model the price effects of steel price shocks on stock returns. For the US, they concluded that the stock returns are not significantly affected by steel price shocks. For steel commodities, the opposite was found as steel price shocks have a significant impact on the stock returns. This thesis not only discusses price effects but also of the effects of volatility between the stock markets of China and the US and steel markets.

The literature discussed shows that numerous research has been done on volatility spillovers and market integrations between precious metals and crude oil prices. A lot of the research focusses on commodities like gold, oil and non-ferrous metals. Furthermore, the effects of commodity prices in one country on another country have not been discussed extensively. Research on the price effects of shocks of the Chinese and US stock markets of the global steel price already exists. This thesis fills the gap in research where the volatility spillover of the Chinese and US stock markets on the Countries own steel market of one another is studied.

3. Data

This study uses a sampling period that runs from 06-01-2012 to 06-04-2020. This starting date was chosen because the index for the steel prices exists since that date. A total of 432 weekly observations are obtained for each variable. This study utilizes the returns of stock markets in China and the US. For both China and the US an index will be used. For China, the Shanghai Stock Exchange composite index is used (SSE Composite Index). The SSE Composite Index contains the stocks of all the stocks exchanged on the Shanghai Stock Exchange. For the US, the Standard & Poors 500 index is used (S&P 500). The S&P 500 consist of the 500 companies with the largest market cap in the US. For the steel prices the indices from Steelhome are used. Steelhome is a professional information and news supplier for the Chinese steel industry. Steelhome calculates indices for the steel prices in different countries. This study uses the Steelhome Steel Price Index China and the Steelhome Steel Price Index America, which is the steel price index for the US. The price index consists of the prices of flat and long steel products. Again, the returns of the index are used. All data is obtained from Thompson Reuters Datastream.

The data retrieved from Datastream are the daily prices of the indices which will have to be converted to returns. This is done in equation 1.

$$(1) \qquad R_t = (P_{t-1} - P_t)/P_{t-1}$$

Descriptive statistics and tests for skewness, leptokurtosis and autocorrelation for all return series are shown in table 1. The stock markets have an average positive return over the observation period. The steel price indices have a negative average return. Notable is that the median for the steel prices is zero because in some weeks the price of the index did not change. The unconditional variance or the standard deviation of the returns is similar for the steel prices in China and the US and for the SSE Composite Index. The S&P 500 is clearly the most volatile index of all the return series. The steel prices in the US is the least volatile series. The SSE Composite Index and the S&P 500 both have negative skewness. This implies that extreme positive observations are present. This can be attributed to the positive average mean of the return series of the stock markets. The Steel prices in China and the US show positive skewness, which implies that there are extreme negative observations. This can be attributed to the negative average mean of the return series. Kurtosis measures the

Table 1

Descriptive Statistics

	SSE Composite	S&P 500	Steel China	Steel US
Mean	0.0007	0.0018	-0.008	-0.0007
Median	0.0023	0.0033	0.000	0.000
Min.	-0.1429	-0.1623	-0.1096	-0.0781
Max.	0.0907	0.1142	0.1625	0.1410
Std. deviation	0.0291	0.1142	0.0206	0.0163
Skewness	-0.8825	-1.4999	2.1082	1.5226
Kurtosis	6.6051	16.4086	21.1062	21.1784
Jarque Bera test	292.0299 (<0.001)	3421.8 (<0.001)	6264.2 (<0.001)	6157.5 (<0.001)
ARCH LM test	23.0180 (<0.001)	53.1546 (<0.001)	1.1514 (0.2833)	4.9837 (0.0256)
LBQ (5)	5.7191 (0.3345)	10.3817 (0.0651)	28.5675 (0.000)	108.5520 (0.000)
LBQ (10)	10.4415 (0.4027)	13.6034 (0.1919)	28.9594 (0.0013)	120.1729 (0.000)
LBQ (15)	19.1188 (0.2084)	15.0504 (0.4478)	31.3173 (0.0080)	121.1439 (0.000)
$LBQ(5)^2$	114.9643 (0.000)	229.6023 (0.000)	40.9287 (<0.0001)	26.9304 (0.0001)
$LBQ(10)^2$	218.3686 (0.000)	240.0652 (0.000)	55.8693 (<0.0001)	31.7812 (0.0004)
$LBQ(15)^2$	245.32.68 (0.000)	240.6101 (0.000)	56.2493 (<0.0001)	32.6482 (0.0052)

Notes. p-values are noted in the brackets. The p-values for the ARCH test for heteroscedasticity autocorrelation, the Jarque Bera test for normality, and the Ljung Box test for autocorrelation are listed in parentheses. LBQ specifies the Ljung box test for the returns and LBQ^2 *specifies the Ljung box test for squared returns.*

peakedness and tail distribution of the probability distribution against the normality distribution. All the return series have a positive kurtosis which shows that all series are high peaked and have heavy tails. They show a leptokurtic distribution. Next the Jarque Bera test for normality is done (Jarque & Bera, 1980). The Jarque Bera test tests whether the return series are normally distributed by combining skewness and kurtosis in a test. For all of the series the null hypothesis for normality can be rejected since the p-values of the test are all highly significant.

Because the data are time series, tests for autocorrelation need to be done. First the ARCH LM test from Engle is performed. It is a LaGrange multiplier test to test for the autoregressive conditional heteroscedasticity effects (Engle, 1982). The ARCH test is rejected for all the return series except for the Chinese steel prices. This means that there is no time varying conditional variance in the return series of the stock prices and of the steel prices in the US. Next the Ljung box tests for autocorrelation are done. The Ljung Box test tests for autocorrelation up until lag h. In this study tests will be done on 5, 10 and 15 lags. The test is done on returns and squared returns (Ljung & Box, 1978). The returns of the SSE Composite Index and the S&P 500 show no signs of autocorrelation. The returns of the steel prices of both countries do show significant autocorrelation at all tested lags. The squared returns are significantly autocorrelated for all series at all lags tested. This implies that there are significant ARCH effects. Therefore, lags will have to be used to model the data. No tests for stationarity are conducted since returns are used in this study, these are widely known as being stationary.

4. Methodology

A multivariate GARCH model will be used to model the volatility spillover. These models are necessary to model for volatility spillover in cross sectional time series because the covariance between variables in multivariate GARCH models move over time. In this study the specific multivariate GARCH model, the BEKK-GARCH model by Engle and Kroner (1995) is used.

4.1 VAR model

First a multivariate vector autoregressive (VAR) model by Sims (1980) is specified to model the returns for each of the stock markets and steel prices. This is called the equation for the mean in the VAR-BEKK-GARCH specification. First the number of lags to use in the vector autoregressive equation will have to be determined. This will be determined by modelling the full VAR model and calculating maximum likelihood model estimators. The minimum Aikaike Information Criterion (AIC) and the minimum Bayesian Information Criterion (BIC) are used. The AIC indicates how well the model fits the data without overfitting the data (Aikaike, 1974). Both the AIC and BIC use a penalty term for adding parameters. The BIC has a bigger penalty for using too many parameters (Schwarz, 1978). The AIC does not directly depend on the sample size whereas the BIC does.

Table 2

VAR lag order selection criteria

Lag	AIC	BIC
0	-8.4841	-8.4678*
1	-8.4998*	-8.4183
2	-8.4881	-8.3374
3	-8.4582	-8.2463
4	-8.4424	-8.1652
5	-8.4424	-8.0646

*Notes. AIC specifies the Aikaike Information Criterion, BIC specifies the Bayesian Information Criterion. * indicates the lag order chosen by the information criterion.*

The AIC and BIC scores for the VAR up to 5 lags are presented in table 2. The lowest AIC score is at lag 1 and the lowest BIC score is at lag 0. Since the AIC does not directly depend on the sample size and a relatively small sample size is used the AIC selection criteria is used. This means that Lag 1 will be chosen. The model becomes a VAR(1) model. The model is specified in formula 2 as follows.

$$(2) \qquad R_t = \mu + \sum_{i=1}^{k} \Gamma_i R_{t-1} + \epsilon_t$$

Where R_t are the returns of the stock markets and the steel prices in China and the USA. Let $R_t = [R_{MCt}, R_{Mut}, R_{SCt}, R_{SUt}]$, where $\epsilon_t = [\epsilon_{MCt}, \epsilon_{Mut}, \epsilon_{SCt}, \epsilon_{SUt}]$. Γ_i is a 4 by 4 coefficient matrix and μ is the parameter vector of the mean.

4.2 BEKK-GARCH model

A multivariate GARCH model is used to model the volatility spillover. These models are necessary to model for volatility spillover in cross sectional time series because the covariance between variables in multivariate GARCH models move over time. In this study the specific multivariate GARCH model, the BEKK-GARCH model by Engle and Kroner (1995) is used. The BEKK-GARCH model guarantees that the H_t matrix is positive definite, unlike the VECH model from Bollerslev, Engle and Wooldridge (1988) in which the variance covariance matrix H_t is not always positive. To be able to guarantee positive definiteness of the BEKK-GARCH model the $H_t$variance covariance matrix needs to be positive definite. This is done by adding the constant matrix W to the model. The W matrix adds nothing to the model but the positive definiteness (Engle & Kroner, 1995).

The residuals ϵ_t for each R_t from equation 2 are used to model the conditional variance covariance matrix of the residuals H_t. This is defined in formula 3.

$$(3) \qquad \epsilon_t | \varphi_{t-1} \sim N(0, H_t), \ H_t = \begin{bmatrix} h_{11,t} & \cdots & h_{14,t} \\ \vdots & \ddots & \vdots \\ h_{14,t} & \cdots & h_{44,t} \end{bmatrix}$$

Where the residuals ϵ_t for each of the returns of the stock markets and the steel prices are the residuals of the VAR model in equation 2. φ_{t-1} contains all the information until time $t-1$. Assumed is that the residuals ϵ_t are normally distributed and have a zero mean. Using the BEKK-GARCH (1,1) model the conditional variance covariance matrix specifically becomes the following:

$$(4) \qquad H_t = W'W + A'H_{t-1}A + B'\epsilon_{t-1}\epsilon_{t-1}'B$$

Where H_t is the 4 by 4 conditional variance covariance matrix of the residuals, the assumption is made that H_t is a symmetric matrix. A and B are defined as the 4 by 4 matrices of the parameters and W being the upper triangle matrix of the parameters. A being the matrix which captures the ARCH effects which are the effects of shocks on the conditional variance. And B being the matrix which captures the GARCH effects which are the effects on the volatility coming from one residual variance lags.

The parameters in the BEKK-GARCH model can be estimated by maximizing a Log likelihood function. For T observations and N variables the function is given by

$$(5) \qquad \ell(\theta) = -\frac{TN}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(ln|H_t| + \epsilon_t' H_t^{-1}\epsilon_t)$$

Where H_t is the conditional variance covariance matrix and θ is the number of unknown parameters to be estimated.
The full unrestricted model of equation 4 can be written by matrix multiplication. Equation 4 is written in matrices in equation 6.

$$(6) \qquad H_t = \begin{bmatrix} w_{11} & 0 & 0 & 0 \\ w_{12} & w_{22} & 0 & 0 \\ w_{13} & w_{23} & w_{33} & 0 \\ w_{14} & w_{24} & w_{34} & w_{44} \end{bmatrix} \begin{bmatrix} w_{11} & w_{12} & w_{13} & w_{14} \\ 0 & w_{22} & w_{23} & w_{24} \\ 0 & 0 & w_{33} & w_{34} \\ 0 & 0 & 0 & w_{44} \end{bmatrix} +$$

$$\begin{bmatrix} a_{11} & \cdots & a_{41} \\ \vdots & \ddots & \vdots \\ a_{14} & \cdots & a_{44} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & \cdots & h_{14,t-1} \\ \vdots & \ddots & \vdots \\ h_{14,t-1} & \cdots & h_{44,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & \cdots & a_{14} \\ \vdots & \ddots & \vdots \\ a_{41} & \cdots & a_{44} \end{bmatrix} +$$

$$\begin{bmatrix} b_{11} & \cdots & b_{41} \\ \vdots & \ddots & \vdots \\ b_{14} & \cdots & b_{44} \end{bmatrix} \begin{bmatrix} e_{1,t-1}^2 & \cdots & e_{1,t-1}e_{4,t-1} \\ \vdots & \ddots & \vdots \\ e_{4,t-1}e_{1,t-1} & \cdots & e_{4,t-1}^2 \end{bmatrix} \begin{bmatrix} b_{11} & \cdots & b_{14} \\ \vdots & \ddots & \vdots \\ b_{41} & \cdots & b_{44} \end{bmatrix}$$

The squared elements of the A matrix present the relationship of the variance with its own variance. This gives the effects of shocks on the variance in the past on the variable's current variance, these elements are the diagonal elements $[a_{11}, a_{22}, a_{33}, a_{44}]$. These coefficients measure the short-term volatility persistence as well (Basher & Sadorsky, 2016). Moreover, this model allows for the calculation of the shocks and effects on variance across variables, these elements are all the non-diagonal elements. The squared elements of the B matrix present the shocks of past volatility on the current volatility. These effects can be observed not only on the variable's own past volatility but also across variables. The elements that present the effects on a variable's own volatility are given by the diagonal elements $[b_{11}, b_{22}, b_{33}, b_{44}]$. Additionally, these elements measure long-term volatility persistence. The elements of the B matrix that give an indication for the effects across variables are important to measure the spillover effects. These elements are the non-diagonal elements. For the conditional mean equations Γ_i is used to capture the mean spillovers between the variables. With the elements in the Γ_i matrix the effects of a variables' past returns on the current returns are captured.

4.3 Tests for volatility spillover

In addition to the significance of the coefficients that come forward from the VAR-BEKK-GARCH model an additional test for volatility spillover shall be done. The coefficients a_{ij} and b_{ij} present the effect of past shocks on variance across variables and the shocks of past volatility on current volatility respectively. To test the significance of existence of volatility spillover the null hypothesis that both coefficients are equal and equal to zero has to be rejected. Therefore, a joint test of two parameters that are zero needs to be rejected. The null hypothesis to test for Volatility spillovers from the American stock market to the Chinese stock market is the following:

$$H_0: a_{12} = b_{12} = 0$$

The null hypothesis test to test volatility spillover from the Chinese stock to the American stock market is the following.

$$H_0: a_{21} = b_{21} = 0$$

The hypothesis will be tested using the Wald test. The Wald test uses the parameter coefficients and the diagonal of the variance covariance matrix of the BEKK model. The Wald test follows a chi-square distribution (Kodde & Palm, 1986).

5. Results

In this section, the empirical results of the VAR-BEKK-GARCH model are discussed. The VAR-BEKK-GARCH model is estimated to measure the return and volatility spillover between the stock markets of China and the US and the steel prices in China and the US.

5.1 Conditional mean estimates

Table 3 represents the results of the VAR(1) conditional mean equation. The conditional return intercepts μ are only significant for the stock returns in the US. The coefficient found is 0.0019. Regarding own mean spillover effects, steel prices in China and the US show significant spillover effects from their own lagged terms. Γ_{33} and Γ_{44} both have a highly significant coefficient of 0.2329 and 0.2527 respectively. Shocks on steel prices in the

Table 3

VAR(1) Parameter estimations of the conditional mean equation

Variable	coefficient	t-statistic
μ_1	0.0002	0.1658
μ_2	0.0019*	0.0609
μ_3	-0.0005	0.5612
μ_4	-0.0005	0.5105
Γ_{11}	0.0518	1.0453
Γ_{12}	0.1178*	1.7424
Γ_{13}	-0.0638	-0.9476
Γ_{14}	-0.0671	-0.7820
Γ_{21}	0.0009	0.0272
Γ_{22}	-0.0775	-1.5596
Γ_{23}	-0.0404	-0.8169
Γ_{24}	-0.0336	-0.5342
Γ_{31}	0.0378	1.0998
Γ_{32}	0.0070	0.1495
Γ_{33}	0.2329***	4.9892
Γ_{34}	0.0762	1.2824
Γ_{41}	-0.0671	-0.7820
Γ_{42}	-0.0336	-0.5342
Γ_{43}	0.0762	1.2824
Γ_{44}	0.2527***	5.3873

*Notes. *, **, *** represent significance at a significance level of 10%, 5% and 1% respectively.*

past have positive effects on the current steel prices. This shows that there is some evidence of short term predictability of the returns of steel prices in China and the US. Own mean spillover effects are not found for the stock markets of China and the US. This is in line with the weak form of the efficient market hypothesis by Fama (1970). Which states that with technical analyses past price movements cannot influence current prices. However, the weak form of the efficient market hypothesis does not hold for the steel prices of China and the US because the own past returns influence current returns. Regarding the non-diagonal coefficients, it becomes clear that there is only one significant coefficient, that is Γ_{12}. This coefficient shows that an increase in the price of the US stock market leads to an increase in the price of the Chinese stock market. This implies that positive shocks to the US stock market lead to one week ahead positive returns on the Chinese stock market. This is in line with research conducted by Wang and Wang (2010) about price and volatility spillovers between greater China markets and the developed markets of the US and Japan. All in all, there are no further cross series relations between the steel prices and the stock markets. Only the steel prices depend on its own lagged returns. Gutierrez and Vianna (2018) found different results in their study about price effects of steel commodities. They found that both the Chinese and US stock market influence the steel market. However, in their research the data of the global steel market and not data of specific steel markets on national level is used.

5.2 Conditional variance estimates

Table 4 represents the results of the full BEKK(1,1) conditional variance equation. For the constant W all the coefficients are significant except for W_{11} and W_{32}.
The parameters of the matrix A capture the ARCH effects. The diagonal parameters of the Chinese stock market and the US steel price, A_{11} and A_{44} respectively show significant coefficients of 1%. This means that the variables own past shocks have an effect on the current conditional variance. Thus, a positive shock in the variables own past leads to an increase in the current conditional variance of the parameters A_{11} and A_{44}. The effects of shocks on conditional variance across series can be determined with the non-diagonal parameters of the A matrix. The highly significant coefficient A_{21} shows that a positive shock to the Chinese stock market leads to an increase in the conditional variance of the stock returns of the US market. A negative significant spillover effect is found between the Chinese stock and steel markets. Implying that a positive shock on the Chinese stock market leads to a decrease in conditional variance of the steel prices. A significant spillover can also be

observed for coefficient A_{42}. Implying that a shock on the US stock market has a positive effect on the US steel prices.

The parameters of the matrix B capture the GARCH effects. All the diagonal coefficients (B_{11}, B_{22}, B_{33}, B_{44}) are significant and have a positive effect. This means that a shock on the variables own past volatility leads to an increase in the current periods volatility. All the other coefficients are significant except for B_{41} which implies that there is no volatility spillover from the Chinese stock market to the US steel market. For all the other coefficients, there are significant bidirectional spillover effects except for spillover between the Chinese stock market and the US steel market. The bidirectional volatility spillover between the stock markets of China and the US is in line with research by Yu et al. (2019). All spillovers to the Chinese stock and steel market are negative. On the contrary, almost all spillovers to the US stock and steel market are positive. This means that positive shocks in the past from the other markets on the Chinese stock and steel markets lead to a negative shock in the current period. For the US stock and steel market a positive shock in the past from the other markets leads to a positive shock in the current period.

Table 4

BEKK(1,1) Parameter estimations of the conditional variance equation

variable	Coefficient	t-statistic
W_{11}	0.0004	0.3652
W_{12}	0.0272***	47.7194
W_{22}	-0.0684***	-86.1271
W_{31}	0.0215***	25.7683
W_{32}	0.0004	0.2513
W_{33}	-0.0188***	-7.9342
W_{41}	-0.0056***	-9.8011
W_{42}	0.0051***	12.9698
W_{43}	-0.0119***	-39.1562
W_{44}	0.0262***	46.9215
A_{11}	0.0343***	3.0169
A_{12}	-0.0348	-1.0903
A_{13}	0.0156	0.2228
A_{14}	0.0817*	1.8901
A_{21}	0.0682***	3.2133
A_{22}	0.0205	0.5844
A_{23}	-0.0153	-0.2808

A_{24}	0.0146	0.1105
A_{31}	-0.0469**	-2.2666
A_{32}	0.0475	0.8223
A_{33}	0.0119	0.1285
A_{34}	0.0407	0.3587
A_{41}	0.0350	0.9649
A_{42}	0.0942***	2.8949
A_{43}	-0.0130	-0.1628
A_{44}	0.0888***	2.7156
B_{11}	0.9514***	137.6468
B_{12}	-0.0252***	-8.5457
B_{13}	-0.0270***	-13.3448
B_{14}	-0.0150***	-5.7382
B_{21}	0.0400***	8.0081
B_{22}	0.9529***	420.5723
B_{23}	-0.0256***	-15.2141
B_{24}	0.0592***	22.3219
B_{31}	-0.0259**	-2.1629
B_{32}	-0.0133***	-3.7447
B_{33}	0.9651***	293.1116
B_{34}	-0.0502***	-13.3835
B_{41}	-0.0075	-0.8271
B_{42}	0.0116**	2.2652
B_{43}	0.0308***	8.8843
B_{44}	0.9285***	224.2222
LL	0.024	

*Notes. *, **, *** represent significance at a significance level of 10%, 5% and 1% respectively.*

5.3 Empirical results tests for volatility spillover

Finally, the tests for volatility spillover are conducted. The outcome of the Wald tests on the coefficients of the parameters are shown in table 5. The results indicate that there is volatility spillover between all the tested spillover relations except for volatility spillover from the Chinese stock market to the US steel market. All the parameters that show significant results in the BEKK model also show significant volatility spillover with the Wald test. The results indicate that there is a bidirectional spillover between all the stock markets and steel markets. The only exception is the insignificance of a spillover between The Chinese stock market and the US steel market. Thus, a unidirectional spillover is present from the US steel market to the Chinese stock market.

Table 5.

Wald test for volatility spillover

Null hypothesis		Wald Statistic	p-value	conclusion
$H_0: a_{12} = b_{12} = 0$	S&P 500 has no volatility spillover on SSE	76.1714	0***	reject
$H_0: a_{21} = b_{21} = 0$	SSE has no volatility spillover on S&P 500	70.8764	<0.0001***	reject
$H_0: a_{13} = b_{13} = 0$	Chinese steel has no volatility spillover on SSE	178.7015	0***	reject
$H_0: a_{31} = b_{31} = 0$	SSE has no volatility spillover on Chinese steel	7.5381	0.0231**	reject
$H_0: a_{14} = b_{14} = 0$	US steel has no volatility spillover on SSE	33.3319	<0.0001***	reject
$H_0: a_{41} = b_{41} = 0$	SSE has no volatility spillover on US steel	4.8911	0.0867*	Do not reject
$H_0: a_{23} = b_{23} = 0$	Chinese steel has no volatility spillover on S&P 500	235.2709	0***	reject
$H_0: a_{32} = b_{32} = 0$	S&P 500 has no volatility spillover on Chinese steel	21.8832	<0.0001***	reject
$H_0: a_{24} = b_{24} = 0$	US steel has no volatility spillover on S&P 500	688.8320	0***	reject
$H_0: a_{42} = b_{42} = 0$	S&P 500 has no volatility spillover on US steel	24.9807	<0.0001***	reject
$H_0: a_{34} = b_{34} = 0$	US steel has no volatility spillover on Chinese steel	236.0322	0***	reject
$H_0: a_{43} = b_{43} = 0$	Chinese steel has no volatility spillover on US steel	89.1367	0***	reject

*Notes. *, **, *** represent significance at a significance level of 10%, 5% and 1% respectively.*

6. Conclusion

This thesis examines effects of return and volatility spillover between the stock markets and steel markets of China and the US. The full VAR-BEKK-GARCH model by Engle and Kroner (1995) is used to model the spillovers between all return series examined. The dataset consists of weekly returns of the Chinese and US stock markets and steel markets from week one of 2012 to week fifteen of 2020. First a VAR(1) model is used to model the return spillover after which the BEKK(1,1)-GARCH model is used to model the volatility spillover. Finally tests for volatility spillover are performed to test the significance of the effects. The empirical results show that return spillover effects only exist for the Chinese and US steel markets own past returns and for a return spillover from the US stock market to the Chinese stock market. Similar results can be seen in a previous study by Wang and Wang (2016). However, the results in this study contradict with research by Guitierrez and Vianna (2018). Regarding volatility spillovers the BEKK-GARCH model gives empirical evidence of bilateral volatility spillover between almost all return series. No evidence for a spillover from the Chinese stock market to the US steel market was found. The presence of a bidirectional volatility spillover between the Chinese and US stock market is in line with previous research by Yu et al. (2019).

Following the empirical results specified above the research question: *How do the returns and volatility between steel prices and the stock markets of China and the US interact?,* can be answered. The returns of most steel and stock markets do not interact with each other except for a weak positive interaction between the Chinese stock market and the US steel market. Although there is almost no return interaction between the markets studied, there is volatility interaction between almost all markets studied. Both positive and negative volatility interaction effects can be observed between nearly all markets. The only exception where no volatility spillover exists, is a spillover from the Chinese stock market to the US stock market. Concluding, there exists almost no interaction between the returns of the markets observed but between almost all markets there is interaction between the volatilities.

One of the shortcomings of this study is that weekly data was used. This means that less observations are used in the models in comparison to when daily returns would be used. This could also be an explanation for the contradicting results regarding the return interaction of Chinese and US stock market and steel markets in comparison to the study done by Guitierrez and Vianna (2018). Another reason for the contradiction could be the different sample periods used in the studies. In future research, sub-periods should be used to be able to observe how the return and volatility interaction would change over time. Another recommendation for future is research is that it should be researched why the steel markets do not follow the weak form of the efficient market hypothesis. Finally, in the future it should be researched why shocks to the Chinese markets lead to negative volatility spillover effects and shocks to the US markets lead to positive spillover effects.

7. References

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