Erasmus University Rotterdam

Erasmus School of Economics

Bachelor Thesis Economie & Bedrijfseconomie (Financial Economics)

Commodity returns and their relationship to stock market volatility

Name student: Hidde Bouwhuis

Student ID number: 494492

Supervisor: Bhuyan, A

Second Assessor: X

Date final version: 24/06/2021

Abstract

In this paper, data was gathered regarding the prices of various commodities and changes in U.S. stock market volatility in order to shed light on the relationship between commodity prices and stock market uncertainty. It was hypothesized that the correlation between both variables is strong and that some commodities would benefit from an increase in stock market volatility, while others would not. Other hypotheses stated that commodity returns will not be strongly correlated to each other and that both commodity returns and changes in stock market volatility can be used to predict the other variable. Based on an analysis using correlation coefficients and VAR[1] models, four main conclusions were drawn: (i) commodities cannot be considered a homogenous asset class. (ii) Commodity returns Granger-cause and are Granger-caused by changes in stock market volatility. (iii) Most forecasts based on this Granger-causality outperform forecasts based on historical averages. (iv) Commodity returns are negatively and weakly correlated to changes in stock market volatility. While it was found to be true that commodity returns are significantly correlated to changes in stock market volatility, this relationship was predominantly negative and, based on the correlation coefficients, cannot be considered strong. This means that while the two hypotheses regarding the correlation between commodities and the fact that they can forecast (and be forecasted by) changes in stock market volatility were, for the most part, confirmed, the main hypothesis was disproven.

Table of contents

1 Introduction

Commodity markets have existed for as long as civilizations have traded with each other. Before the Amsterdam Stock Exchange sold its first security in 1602, it functioned as a commodities market (Stringham 2003). In fact, it is thought that commodity trading has existed as far back as 4,500 BC in ancient Mesopotamia (Banerjee 2013). Entire empires, such as the Dutch colonial empire and the British empire, have risen and fallen in the pursuit of more trade opportunities to enrich themselves. Nowadays, global financial trade has shifted largely to the trade of securities such as stocks and bonds, but commodity markets still generate hundreds of billions of dollars in volume each year. However, in the modern day commodities have taken up a new role in the financial landscape. Most investors tend to see commodities as a store of value as opposed to an asset that will provide them with high returns in the short-term. A general consensus among investors is that people tend to flock to commodities in times of uncertainty, with renowned investor Warren Buffet even stating that 'Gold is a way of going long on fear'. This paper aims to determine the veracity of that vision, with the following question serving as the main research question (using U.S. data):

To what extent are commodity returns related to changes in stock market volatility?

There already exists a lot of literature on the relationship between the commodity market and the stock market. Two of the more broad investigations into this relationship are Creti et al. (2013) and Kang et al. (2020). In the first paper, the relationship between the stock market and 25 different commodities was examined. The researchers came to the conclusion that stock market returns and commodity returns are indeed correlated, with the degree of correlation varying over time. The second paper looked at the dynamics of global stock market volatility and commodity prices. Among other things, it found that stock market volatility and commodity prices impact each other and that this effect is especially significant during global financial crises. Other papers are usually a bit more specific and tend to focus on the relationship between the stock market and a specific commodity. This includes Sadorsky (1999), Papapetrou (2001) and Vo (2011), all three of which focussed on the link between oil and the stock market. While the effect of the returns on oil on stock market returns (and vice-versa) was the focal point of both Sadorky's and Papapetrou's research, Vo put more emphasis on the volatility in both markets and how they affect each other. All three papers come to the conclusion that the oil market and the stock market are strongly correlated with regards to both price (returns) and volatility. Papers on other commodities include Smith (2001) and Mishra et al (2010), which came to contradicting conclusions regarding the relationship between the stock market and gold prices.

The aforementioned papers largely focussed on the correlation present in both markets. While this is interesting enough, one might also wonder if one market can be used to predict the other. Papers which delved into the predictive power of one market relative to the other include Salisu et al. (2019), which found commodity prices to be good predictors of stock market returns and Liang et al. (2020), which determined that commodity price volatility can be used to predict the realized volatility of the S&P 500.

In conclusion, this paper is not the first paper to delve into the relationship between commodity markets and the stock market. However, the particular effect the main research question proposes, has gone largely unresearched. That is why this paper will be scientifically relevant.

Furthermore, this paper could be practically relevant to many investors. If there is indeed a significant relationship between stock market volatility and returns on various commodities, individual investors and organisations such as hedge funds could use that information to better understand and anticipate price movements in commodity markets. Whether investors could actually use this information to increase their returns, remains to be seen. McLean & Pontiff (2016) showed that portfolio's based on trading strategies published in papers suffer a significant loss in returns after publication, indicating that relationships observed in financial markets disappear at least partly post publication. However, whether or not that will happen to any effect observed between stock market volatility and commodity returns is beyond the scope of this paper and is up to other researches to investigate further.

1.1 Sub-questions and report outline

To support the main research question, this paper will also aim answer the following sub-questions:

Sub-question 1: What are some key characteristics of commodities and commodity markets?

To understand this paper, one should have a firm grasp of what commodities are and how they are traded. The first sub-question aims to provide readers with a solid base to make sure they have at least the basic knowledge required to really understand this paper

Sub-question 2: To what extent are the returns of various commodities related to each other?

This second sub-question is about whether or not the returns of various commodities are correlated or not. This question is interesting for a couple of reasons. First of all, if we assume that it is indeed true that investors 'flee' to commodities during times of uncertainty, returns should be correlated across different commodities. If this is not the case, investors apparently have reason to prefer some commodities over others during times of high volatility. Why investors prefer those commodities over others could then be an interesting question to research further in another paper. Secondly, if the various commodities are all (strongly) correlated to each other, there would have to be some central force driving all commodity prices up, or down, simultaneously. Uncertainty in the stock market is one of the most likely candidates to be that driving force, making answering the research question a lot easier.

Sub-question 3: Can future commodity returns be predicted by current changes in stock market volatility (and vice-versa)?

The last sub-question wants to determine whether or not stock market volatility can be used to predict future commodity returns, assuming the two are related. While finding a strong correlation between commodity returns and stock market volatility is interesting in and of itself, discovering a consistent predictor for commodity returns would be much more fascinating. Firstly because if stock market volatility has a delayed effect on commodity returns, it could imply inefficiencies in the commodities market. How and why these inefficiencies exist would then be an interesting premise for further research. Secondly, if changes in stock market volatility do indeed predict commodity returns, that information could be used by traders to develop new trading strategies more focussed on the commodities market.

After this introduction, the theoretical framework will follow, which will, among other things, aim to answer sub-question 1 and provide a more in-depth analysis of the related literature. Chapter 3 will give a short summary of my own hypotheses for the main research question and sub-questions 2 and 3, based on the discussed literature. Chapter 4 will discuss both the data and methodology required to answer the research questions and the aforementioned sub-questions. After the results have been discussed and the relevant questions have been answered, a conclusion will follow.

2 Theoretical Framework

2.1 Commodities

2.1.1 What is a store of value?

In the introduction it was stated that nowadays, most investors see commodities as stores of value rather than an asset that will generate high returns in the short term. Before we examine what exactly constitutes a commodity, it might be a good idea to take a look at what a store of value is first.

If something is said to be a store of value, it means that the asset in question maintains its value (purchasing power) over a long period of time (Corporate Finance Institute, n.d.). A good store of value is any asset that can be held and later converted to money relatively quickly without losing its value in the process. In practice, this means that an asset can be considered a store of value if it can be easily stored, has a solid underlying demand and does not deteriorate over time.

The most obvious store of value is money (Mankiw 2020). Money fits all three of the aforementioned characteristics of a good store of value perfectly, so why do people even bother with other stores of value?

The main answer to this question is quite simple: inflation. During the second half of the twentieth century, especially during the 1970s, a period during which the U.S. experienced some of their highest inflation in recent history, inflation and its effects were seen as the most serious issue faced by financial markets and their participants (Lintner 1975). To prevent inflation from eating away at their wealth, investors seek investments that have zero (or at least a reduced) possibility of having a real return below zero, meaning their purchasing power does not decline (Bodie 1976). Assets that can hedge against inflation include common stocks, real estate, fixed income securities (such as bonds) or commodities (such as gold) (Arnold & Auer 2015; Bird 1984). So, it could be argued that the raison d'être for commodities for the average investor is to provide them with a store of value that retains its purchasing power and therefore hedges them against inflation.

2.1.2 What is a commodity?

The previous section has made it clear that investors seek stores of value other than money because money loses its value due to inflation. That is where commodities come into play. This section will explore what exactly a commodity is.

Commodities are economic goods, mainly natural resources and agricultural products (Kennon, 2020). The main characteristic of a commodity is fungibility, which means that commodities of the same grade are considered equal. For example, an investor buying a kilogram of gold will not care whether the gold was dug up in South Africa or in Russia, as long as the fineness (quality) is equal.

Commodities can be divided into many different categories. The most common division of commodities into different categories is the distinction between hard commodities and soft commodities. Hard commodities are natural resources, such as gold or oil, while soft commodities are agricultural products and livestock, such as corn or sugar (Corporate Finance Institute, n.d.).

2.1.3 Commodity markets

Just like any other market, commodity markets are driven by supply and demand. Commodities can be traded in various ways. Investors could buy and sell the actual physical commodity, or they could trade derivates based on an underlying physical commodity. Because trading physical commodities is very cumbersome and not at all realistic for most market participants (e.g. you cannot expect an individual investor who wants to buy 1,000 barrels of crude oil to actually store that oil somewhere at their house), most commodities trading happens via futures contracts.

Commodities trading can happen via an exchange, like the New York Mercantile Exchange (NYME) or the Chicago Mercantile Exchange (CME), or over-the-counter, when two parties trade commodities (or derivatives based on commodities) without the intervention of a third party.

Section 2.1 has hopefully provided readers with an adequate answer to sub-question 1. We will now move on the section 2.2 which will explore the concept of volatility.

2.2 Volatility

In the introduction, it is stated that this paper wants to examine whether or not the common investor sentiment, that people flock to commodities in times of uncertainty, is true or not. Because stock market uncertainty is an abstract concept that is very hard to measure, this paper uses a proxy for stock market uncertainty. Like many other papers such as Connolly et al. (2005) and Sarwar & Khan (2017), this paper uses stock market volatility as that proxy.

In general, volatility is the measure of the fluctuations of a certain asset's price over time (Corporate Finance Institute, n.d.). Therefore, it can be seen as a measure of the amount of uncertainty or risk related to the asset in question, after all, a higher volatility asset's price can fluctuate significantly more than a lower volatility asset's price.

Volatility is usually measured by taking the standard deviation of an asset's price over a certain period of time. Volatility that is calculated in this manner (i.e. based on past prices) is called historical volatility. The expected volatility in the future can also be calculated based on option prices, which reflect the so-called implied volatility (Kuepper 2021).

2.2.1 CBOE Volatility Index

While the oldest market index, the Dow Jones Transportation Average, dates back to 1884 (Terrel & Vu 2017), volatility indices were first proposed in a 1989 paper from Brenner & Galai. Based on this paper the Chicago Board Options Exchange (CBOE) instructed economist Bob Whaley to calculate values for a stock market volatility index based on the S&P 500. From this, the VIX index was born in 1993, which measures implied volatility based on 30-day out-of-the-money European style S&P 500 call and put options (CBOE 2019). Nowadays, the VIX index is the most common measure of market volatility for the U.S. stock market, it is widely used by both financial market participants and researchers. Both of the aforementioned papers which used stock market volatility as a proxy for uncertainty (Connolly (2005) and Sarwar & Khan (2017)) also used the VIX index as a measure of the stock market volatility.

Calculating the VIX index is a complicated multi-step process. Because this paper does not require readers to fully understand that process, it will not be elaborated on further. A comprehensive guide can be found in the CBOE's whitepaper for the VIX index cited earlier.

2.3 Literature Review

Now that the main concepts, commodities and volatility, have been explained, we can take a look at some literature on the topic of commodities and stock markets. A couple of relevant papers were already commented on in the introduction. In this section, they will be examined further.

The first two papers mentioned, Creti et al. (2013) and Kang et al. (2020), both took a more general approach, looking at multiple commodities instead of focussing on just a small number of them. Creti et al. looked at the correlation between S&P 500 returns and the returns of 25 different commodities. It was found that commodities cannot be considered a homogenous asset class. They could have a positive or a negative correlation with stock market returns, depending on their sector and individual characteristics. Creti et al. also found that the correlations are very volatile, especially after the financial crisis of 2008, during which the correlation of almost all commodities, except gold, and the S&P 500 increased in the short run. Furthermore, oil was observed to be the most correlated to the stock market, while gold was the least correlated.

Related to this study is Kang et al. (2020), which looked at the world's 16 largest economies, instead of just the U.S. economy. The study gathered data from different commodity price indices covering energy, non-energy and precious metal commodities. It constructed a global stock market volatility index based on the stock market volatility present in the nations included in the research. Kang et al. concluded that shocks to commodity prices lead to long-term increases in stock market volatility, while shocks to stock market volatility lead to a short-term decrease in commodity prices. Furthermore, Kang et al. also found that the degree of correlation between commodity and stock markets varied over time and increased during global financial distress, such as the 2008 financial crisis.

For this paper, the most important finding of both papers is that there is indeed a relationship between the markets for various commodities and the stock market. It is also interesting that both papers conclude that the correlation to the stock market for many commodities increases during financial distress, which could mean that gold is unique in it's role as a 'safe-haven' for investors.

Other papers on this topic tend to be more specific in their approach, focussing on individual commodities instead of a wide array of them. By far the two most debated individual commodities are oil and gold. The next two sections will delve into a number of papers which look at those two commodities

2.3.1 Oil

Oil is arguably the most important commodity on earth. It is the main source of energy for most of the world and provides fuel for the ships, airplanes and trucks which carry goods and persons all over the world. It is also the main ingredient in a number of important goods, such as plastic and polyester. The effect that oil prices have on the economy cannot be understated, with economist James Hamilton even stating that oil prices were responsible (to a certain degree) for every economic recession in the U.S. since World War II, bar one recession in 1960, in his widely cited 1983 paper 'Oil and the macroeconomy since World War II'. In this section, we will discuss three papers regarding the relationship between oil and the stock market.

The first paper, Sadorsky (1999), analysed monthly oil prices and monthly S&P 500 returns between January 1947 and April 1996. Sadorsky found that an increase in oil prices lead to lower stock returns for a period of three months, mostly because higher oil prices mean higher production costs for a lot of companies. This concept is one that is also regurgitated in many other similar papers. However, he found little to no evidence for the opposite effect, i.e. stock prices influencing oil prices. A comparable paper, Papapetrou (2001), which performed its research in Greece using monthly data from January 1981 until June 1996, came to he same conclusion.

While both Sadorsky and Papapetrou conclude that stock prices have no significant impact on oil prices, a 2011 paper by Vo did. The study, using daily data between January 1999 and June 2009, looked at the relationship between S&P 500 returns and the price crude oil futures. Apart from the negative effect oil price increases have on stock market returns also observed by Sadorsky and Papapetrou, Vo also found stock returns to have a positive effect on oil prices. He explains this by stating that higher stock returns imply businesses are doing well, which could mean an increase in demand for oil. All in all, it is clear from the existing literature that there exists a strong relationship between oil and the stock market.

2.3.2 Gold

Gold is the other commodity most researchers are interested in. As mentioned in the introduction, gold is generally considered a store of value and a safe-haven for investors. Therefore, you would expect stock market returns to have a negative correlation with gold prices, as opposed to the non-existing or positive effect stock market prices have on oil prices. While this negative correlation was already found by Creti et al., we will consider two papers dedicated entirely to the relationship between gold an stock market returns.

The first paper, Smith (2001), examines the relationship between gold prices and six different U.S. stock indices, including the Dow Jones and the S&P 500. Smith made use of daily, weekly and monthly data from January 1991 until October 2001. While Smith did find a negative correlation between gold price and stock market returns, the effect was very small and exclusively short-term.

The second paper, Mishra et al. (2010), comes to a different conclusion. In this paper, monthly gold prices and stock market returns were gathered in India from January 1991 until December 2009. Just like Smith, Mishra et al. also concluded that there was a small but significant negative correlation between stock market returns and gold prices. However, they also found that there exists a long-term equilibrium, instead of the exclusively short-term relationship Smith observed. Mishra et al. state that this long-term relationship could be caused by the overall low faith Indian investors have in bank deposits, stocks and bonds, and the integral part gold plays in both social and religious customs in India. In contrast, investors in first world countries like America tend to have more faith in bank deposits, stocks and bonds and will therefore sooner forgo gold than their Indian counterparts.

In conclusion, gold behaves differently than oil. But, just like oil, the full extent of the relationship between gold and the stock market is still unknown and researchers have yet to reach a definitive conclusion on it.

2.3.3 Predictive Power

The previous papers discussed have mainly focussed on assessing the extent of the relationship between various commodities and the stock market Whether one can actually be used to actually predict the other, is another question. This section will cover two papers which attempted to answer that question: Salisu et al. (2019) and Liang et al. (2020).

Salisu et al. (2019) collected monthly data on national stock market indices form the G7 countries (Canada, France, Germany, Italy, Japan, UK, USA) and on various commodity categories, such as agriculture, energy and oil, from January 1960 until October 2017. Based on the commodity prices, models were created to predict stock returns. These models actually outperformed stock market prediction based on historical averages.

Liang et al. (2020) performed a similar study in the U.S. They gathered monthly data on the volatility of 19 different commodities and on the realized volatility of the S&P 500 from February 1991 until February 2019. Liang et al. found the volatilities to be positively, albeit weakly, correlated. Only the correlation between oil and the S&P 500 was over 0.4, which is in line with earlier findings of Creti et al., which determined oil to be the most strongly correlated commodity with the stock market. It was also found that any predictive power commodities have, increases during recessions. This makes sense, as we have already seen in Creti et al. (2013) and Kang et al. (2020) that the correlation between the commodity market and the stock market increases during financial distress.

So, based on these two papers we can conclude that you can use commodity market information to predict what happens in the stock market, up to a certain degree. Whether or not the opposite is true, if stock market information can be used to predict what happens in the commodities market, will be tested later in this paper (sub-question 3).

Based on all the literature discussed, we can conclude a couple of things. First of all, while studies and researchers might disagree about the full extent of the correlation between stock market returns (volatility) and commodity returns (volatility), there definitely is a significant relationship between the two. Secondly, commodities are not a homogenous asset class. This idea was presented in the first paper we discussed, Creti et al. (2013), and further proven by the contradictory conclusions drawn regarding the relationship between oil and the stock market and gold and the stock market. This has obvious implications for the rest of this paper, most certainly for sub-question 2. Lastly, while commodity markets can be used to predict the stock market, the opposite is still unclear. There is no current literature on whether or not the stock market can be used to predict the future of the commodities market. This means that answering sub-question 3 is bound to yield some interesting results.

3 Hypotheses

3.1 Sub-question 2: 'To what extent are the returns of various commodities related to each other?'

The literature reviewed in the previous chapter has made it clear that we cannot really consider commodities to be a homogenous asset class (i.e. that all commodities react to changes in the stock market, or changes in general, in the same way). This was already concluded in the first paper we discussed, Creti et al. (2013), and further evidenced by the conclusions drawn in the papers regarding oil and gold. After all, the relationship between oil and the stock market and the relationship between gold and the stock market was found to be rather different. The reason for this was speculated to be about the different purposes each commodity served, with energy-related commodities, such as oil or natural gas, being the most intertwined with the real economy by having such a large impact on production costs. Because of the differences between each commodity observed in the existing literature, I also expect the commodities included in this paper to behave differently from one another. Therefore, my hypotheses regarding sub-question 2 is that we will find only weak correlations between the returns of commodities from different categories (what those categories are will be clarified in the next chapter).

3.2 Sub-question 3: 'Can future commodity returns be predicted by current changes in stock market volatility (and vice-versa)?'

While there exists no real literature about whether or not stock market information can be used to predict commodity prices, we do know that commodity markets can be used to predict stock markets (up to a certain degree). We also know that commodities and the stock market are definitely related to each other, the existing literature proves as much. Therefore, my hypothesis for sub-question 3 is that stock market volatility will have significant predictive power for commodity returns. The reason for this is that I stand by the notion that (most) commodities are seen as stores of value and 'safe-havens' during times of uncertainty. I should note that I expect stock market volatility to have more of an impact of the returns of precious metals, such as gold and silver, than other commodities, mainly due to the fact that they are the most obvious examples of the safe-haven/store of value role commodities can play. For the second part of this sub-question, whether or not commodity returns can predict stock market volatility, my hypothesis is a bit different. I expect some commodity returns to have a certain degree of predictive power for stock market volatility, but not all. Commodities such as oil or sugar play a large role in the production process for some companies, which is why an increase (decrease) in their returns might lead to a rise (decline) in stock market uncertainty. However, I do not expect other commodities such as gold or silver to have a similar impact.

3.3 Research question: 'To what extent are commodity returns related to changes in stock market volatility?'

The wording 'to what extent' is obviously a bit vague. I think the relationship between commodity returns and stock market volatility will amount to the following: First of all, most commodity returns will be significantly and strongly correlated to stock market volatility. Secondly, I think that the correlation will not be the same for all types of commodities. Because the energy related commodities are especially dependent on the demand coming from large companies, such as those in the S&P 500, I think they will be negatively impacted by stock market uncertainty. However, I also believe in the safe-haven role the other types of commodities could play. Therefore I expect those to be positively correlated to changes in stock market volatility.

4 Data & Methodology

4.1 Data

4.1.1 Commodity returns

Before data can start being gathered, the commodities that will be included in this paper have to be chosen. Looking at some previously discussed papers and the commodities their authors chose to include, the choice seems to be mostly up to the researchers own discretion. This paper aims to look at all types of commodities and will therefore include commodities from three different categories: energy, metals and agriculture. To get a better idea of how commodities as a whole are related to the stock market, a commodity index fund will also be included. Table 1 provides a list of all the included commodities in the different categories and the exchange on which they are traded.

This paper will make use of commodity returns instead of commodity prices. Commodity returns will be calculated in the following manner:

$$r_t = \ln \frac{P_t}{P_{t-1}}$$

Price at time t is defined as the intraday average price based on the daily high and the daily low. It will be calculated as follows:

$$P_t = \frac{P_{high,t} + P_{low,t}}{2}$$

Price data of the various commodities used will be gathered from Yahoo Finance. This paper will use daily data from September 1 2000 until December 31 2020. If data starting at September 1 2000 is not available, it will be gathered starting from the earliest possible date it is available. The third column in Table 1 states the date of the first data point from each commodity.

4.1.2 Volatility

To measure volatility, this paper will make use of the VIX index discussed in the theoretical framework. Changes in volatility will be calculated as follows:

$$\Delta V_t = \ln \frac{V_t}{V_{t-1}}$$

Volatility at time t is defined as the intraday average volatility based on the daily high and the daily low. It will be calculated as follows:

$$V_t = \frac{V_{high,t} + V_{low,t}}{2}$$

Data for the VIX will also be gathered from Yahoo Finance starting September 1 2000 until December 31 2020.

One important thing to note is that the Yahoo Finance database is not fully complete for most commodities we will consider. In cases were data is missing from one of the variables included in a calculation, that date will be left out of the calculation entirely. For instance, when calculating the correlation between crude oil returns and heating oil returns, November 27th 2000 has data for heating oil but does not have data for crude oil. Therefore, this date will be left out of the data used to calculate the correlation.

4.2 Methodology

4.2.1 Correlation

In finance, the most common measure for the correlation between two variables is Pearson's correlation coefficient (Fernando 2021). In this paper, there will be two types of correlation calculated. Firstly, to answer sub-question 2, correlation between the returns of the various commodities will be calculated. This will be done in the following manner:

$$\rho_{i,j} = \frac{Cov(r_i, r_j)}{\sigma_i \sigma_j}$$

Secondly, to answer the main research question, correlation between the various commodities and the changes in stock market volatility will also be calculated. This will be done in the following manner:

$$\rho_{i,j} = \frac{Cov(r_i, \Delta V)}{\sigma_i \sigma_{\Delta V}}$$

The correlation coefficient will be a number -1.0 and +1.0, where -1.0 means a perfect negative correlation and +1.0 means a perfect positive correlation. In literature, a correlation coefficient of 0.68 or higher (-0.68 or lower) is considered a strong correlation, while a correlation coefficient of 0.35 or lower (-0.35 or higher) is considered a weak correlation (Taylor 1990).

Each correlation coefficient will also be tested for significance using a t-test. Critical values for this test will be calculated in the following manner (Penn State Eberly College of Science, n.d.):

$$t = \frac{\rho * \sqrt{n}}{\sqrt{1 - \rho^2}}$$

4.2.2 Vector Autoregressive model

To answer sub-question 3, a vector autoregressive model (VAR) will be used. This model is perfectly suited for analysing the effect two time series have on each other, which is exactly what sub-question 3 is after (Sims 1980). The VAR[1] model will look like this:

$$r_{i,t} = \beta_{1,1} r_{i,t-1} + \beta_{1,2} \Delta V_{t-1} + e_{1,t}$$

$$\Delta V_t = \beta_{2,1} r_{i,t-1} + \beta_{2,2} \Delta V_{t-1} + e_{2,t}$$

These two equations will capture the effect changes in volatility have on the returns of commodities, and vice-versa. The reason there is no constant is because the expected value for both returns and changes in volatility is 0.

Before we can start constructing the model however, we have to test whether or not the time series used are stationary. This will be done by using the Dickey-Fuller (DF) test (Dickey & Fuller 1979). For the DF test, the following coefficients will be estimated for each time series:

$$\Delta y_t = a_0 + a_1 y_{t-1} + e_t$$

If a_1 differs significantly from zero, we can state that the series is stationary. If not, we have to difference the series once and test for stationarity again. This process will be repeated until all the series are stationary and we can apply the VAR model.

Once a VAR[1] model has been constructed, a pseudo-out-of-sample forecast will be performed. Returns for the last 500 datapoints will be calculated using the VAR[1] model and compared to their actual value by looking at the mean-squared error (MSE). The MSE is calculated in the following manner:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(r_{i,t} - \hat{r}_{i,t})^2$$

This will then be compared to the MSE of a forecast using the Simple Moving Average (SMA) of the previous 100 observations, which forecasts values like this:

$$r_{i,t+1} = \frac{\sum_{t-99}^{t} r_{i,n}}{100}$$

Based on this comparison, the validity of using changes in stock market volatility to forecast commodity returns can be ascertained. This method of comparing a forecast model to a forecast based on historical averages is common in financial literature (Salisu et al. 2019).

To completely answer the third sub-question, we also have to determine to what extent volatility can be forecasted using commodity returns. This will be done similarly to the forecasting of commodity returns. The last 500 changes in volatility will be calculated based on the VAR[1] model, using different commodities. The MSE for these forecasts will also be compared to the MSE of a volatility forecast based on the SMA method.

5 Results & Discussion

5.1 The correlation between commodities

Sub-question 2: To what extent are the returns of various commodities related to each other?

To answer the second sub-question, correlation coefficients were calculated for each commodity and for each category of commodities. The results can be found in Table 2 and Table 3.

First of all, it should be noted that most of the correlation coefficients are significant. This means that the actual correlation coefficient for most commodities differs from zero. Furthermore, all but three coefficients are positive, meaning that commodities tend to move in the same direction. If this is the case, there very well could be a central force driving the price of all commodity prices up, or down, at the same time. An obvious candidate for this force is uncertainty in the stock market, but this will be tested later.

However, the extent of this correlation is quite limited. Looking a the correlation coefficients in Table 2, only a single coefficient is higher than 0.68, indicating a strong correlation. In fact, just 12 of the 105 correlation coefficients (roughly 11%) were over the threshold of 0.35. this implies that, while there certainly is a significant correlation between the returns of most commodities, this relationship is mostly incidental. Of the 12 correlations that are strong enough to not be considered weak, not a single one was between two commodities of different categories. This confirms my hypothesis for sub-question 2, which stated that there would only be weak correlations between commodities of different categories. To further confirm this hypothesis, the correlation between the average returns of each category was also calculated. In Table 3, the relevant correlation coefficients are displayed, indicating that none of these averages are strongly correlated either. Moreover, these results could be interpreted as being supportive of Creti et al.'s (2013) assertion that commodities cannot be considered a homogenous asset class. A homogenous asset class would almost certainly exhibit a high degree of correlation, which these various commodities do not.

Interestingly, almost all of the non-significant correlation coefficients are regarding heating oil and the various agricultural commodities. There are two possible explanation for this. The first possible explanation depends on the existence of seasonal effects. Heating oil, like its name would suggest, is used for heating houses and businesses. For this reason, heating oil is in much more demand in the winter than in the summer, meaning you would also expect returns for heating oil to be higher during this period. Agricultural futures, such as corn and soybeans, suffer the opposite effect. Prices for corn and soybeans are lower during the winter, because that is when the supply of new crop is the highest (right after the harvesting season in the fall). Prices for these agricultural commodities reach their highs in the summer, right before the new crop production starts, due to uncertainties regarding the upcoming harvest (CME Group, n.d.). If these seasonal effects exists in our data, it could explain the lack of a significant correlation. However, the time series of returns probably wont exhibit these seasonal effects. An alternative explanation is that investors view heating oil differently from the other commodities included in this study. They might prefer other types of oil, such as crude oil, or other completely different commodities to store their wealth. If this is the case, it might make sense for the returns of these commodities to be uncorrelated, as they are bought by different participants of the commodities market at different times.

Another interesting thing about Table 2 is that the other insignificant coefficients appear exclusively related to lean hogs. One possible explanation for this is that lean hog prices dramatically increased in 2014, a bad year for most other commodities, due to the PED virus having a large effect on livestock across the United States (U.S. Department of Agriculture, 2014). This period of lean hog returns going in the opposite direction of most other commodity returns might have caused the low correlation coefficients observed in Table 2.

5.2 The Vector Autoregressive model & forecasts

5.2.1 Building the models

Sub-question 3: Can future commodity returns be predicted by current changes in stock market volatility (and vice-versa)?

As mentioned in the methodology section, we have to make sure the time series used are stationary before the VAR[1] model can be constructed. To test this, DF tests were conducted on every series, the results of which can be found in Table 4.

The results of the various DF tests are quite clear: every time series included in the data is in fact stationary. This means that we can start building the VAR[1] models using the time series and that no data alteration (i.e. differencing) is required. Before we continue to the VAR[1] models, this results also has implications for the previous section. In that section, seasonal effects were given as one possible explanation for the lack of significant correlation coefficients for heating oil. However, stationarity implies that there are no seasonal effects in the time series for commodity returns. This lack of seasonality means that the aforementioned explanation is most likely not true.

The fitted VAR[1] models can be found in Table 5, Table 6 and Table 7. Each model contains coefficients for the following two equations:

$$r_{i,t} = \beta_{1,1} r_{i,t-1} + \beta_{1,2} \Delta V_{t-1} + e_{1,t} \tag{1}$$

$$\Delta V_t = \beta_{2,1} r_{i,t-1} + \beta_{2,2} \Delta V_{t-1} + e_{2,t} \tag{2}$$

The results can be interpreted in the following manner: if the coefficient for changes in stock market volatility in the first equation ($\beta_{1,2}$) is significant, we can state that changes in stock market volatility 'Granger-cause' commodity returns. On the other hand, if the coefficient for commodity returns in the second equation ($\beta_{2,1}$) is significant, we can state that commodity returns Granger-cause changes in stock market volatility. Some variable A Granger-causing some other variable B can be interpreted as follows: while current values of variable A might not directly cause future values of variable B, they do contain information that will predict future values of variable B more accurately than a standard autoregressive model will be able to (Granger 1969). An overview of which commodity returns Granger-cause and/or are Granger-caused by changes in stock market volatility is given in Table 8.

The first table, Table 5, yields a couple of interesting results. First of all, we observe that crude oil returns will decrease when stock market volatility increases and that increases in crude oil returns will lead to an increase in stock market volatility. This result seems to confirm what earlier papers regarding oil already stated (Sadorsky 1999; Papapetrou 2001; Vo 2011): uncertainty around company performances will lead to uncertainty about the future of oil demand, which decreases the oil price. The other way around, increases in the oil price will lead to higher production costs for a lot of companies, which increases uncertainty about their future performance, which raises volatility. Based on the models of the other energy commodities, it seems likely that this same deduction can be about their relation to the stock market as well.

The second table, Table 6, shows the VAR[1] model specifications for the commodities in the metal category. All four metals included in this paper seem to share the same relationship with stock market volatility: increases in stock market volatility negatively impact returns, while increases in returns positively impact stock market volatility. First of all, this result implies that the safe-haven role traditionally attributed to gold, does not exist. Gold returns, like the returns of silver, platinum and copper, suffer the negative effects of stock market uncertainty. If they were a safe haven, you would expect them to thrive in such times, but they clearly do not. Secondly, one possible explanation for the positive relation between the returns on metal commodities and stock market uncertainty is the fact that all four metals have a lot of industrial applications. For instance, copper is used for electrical wiring and gold is used in many electronic devices such as phones and computers. Rising prices could therefore increase production costs, which, similarly to the energy coefficients, leads to uncertainty in the stock market.

The final table, Table 7, looks at the agricultural commodities. The results are similar to the results in the previous two tables. Again, there is not a single commodity which profits from stock market uncertainty. Furthermore, the commodities of which it can be said that they Granger-cause stock market volatility, all have a positive $\beta_{2,1}$ coefficient, similarly to the commodities in the previous two categories.

All in all, based on Table 5, Table 6 and Table 7, it can be concluded that changes in stock market volatility do indeed have predictive power for most commodity returns. While this confirms the hypothesis given in chapter 3, the effect is the opposite of what I expected. It seems to be that current uncertainty in the stock market negatively impacts future commodity markets. This could indicate that during true uncertainty investors prefer having cash over any other financial asset. Furthermore, it is also true that some commodities can be used to predict stock market volatility. There seems to be no real discernible pattern to which commodities Granger-cause stock market volatility and which do not. However, as stated earlier, it could have something to do with which commodities influence production costs for a lot of businesses and which do not.

5.2.2 The forecasts

To test the quality of the forecasts we can now produce using the VAR[1] models, they are compared to forecasts based on historical averages. Tables 9 and 10 show the results of a pseudo-out-of-sample forecast of the last 500 observations for the variable in question. Only commodities which are Granger-caused by stock market volatility are forecasted and stock market volatility is only forecasted by commodities which Granger-cause it (see Table 8).

The results are quite clear, for every commodity (except for the average of the energy commodities) the VAR[1] model is better at forecasting future returns than the simple moving average is. The same model is also better at forecasting future changes in stock market volatility than the simple moving average is.

The analysis used to answer sub-question 3 has a couple of limitations. First of all, this paper only considered VAR[1] models. It could very well be possible that it takes more than one day for stock market information to be fully integrated into commodity markets. Therefore some other VAR[p] model which uses more than one lag could yield different results than the VAR[1] models this paper used. Another limitation arises from the fact that each commodity was considered individually. Earlier, we concluded that the returns of most commodities were in fact significantly correlated (Table 2). We also know that some of these commodities have a significant influence on stock market volatility. This means that almost every VAR[1] model considered suffers from some degree of omitted variable bias. While it is impossible to completely get rid of this bias, there are too many variables that could influence both commodity returns and stock market volatility which therefore cause omitted variable bias. However, it could be reduced by combining every model into one. Whether or not this would cause results to be different and why is a potential topic for future research.

5.3 The correlation between commodity returns and changes in stock market volatility

In the previous section, the relationship between changes in past (future) commodity returns and future (past) changes in stock market volatility was observed. However, to answer the research question fully, we also need to consider the correlation between concurrent commodity returns and stock market volatility. The relevant correlation coefficients can be found in Table 11.

The coefficients in Table 11 further confirm the negative relationship between commodities and stock market volatility. Interestingly enough, there are more significant correlation coefficients than significant coefficients in the various VAR[1] models. This would indicate that stock market information is quickly processed by commodity investors, meaning the earlier suggestion that VAR[p] models would fit the data better is unlikely. Furthermore, the fact all coefficients are negative further proof that stock market uncertainty is not beneficial to commodity markets, contrary to what some investors tend to believe. However, it should be noted that not a single correlation coefficient passes the 0.35 threshold, meaning commodity returns are only weakly correlated to stock market volatility.

All in all, based on all the data and the following analysis, we can formulate the an answer to the research question: '*To what extent are commodity returns related to changes in stock market volatility?*'. Most commodity returns are negatively correlated to stock market volatility. This (weak) negative correlation transcends categories and appears to be present in all types of commodities. The commodity-volatility relationship exists over multiple periods, which means some commodity returns can be predicted by changes in stock market volatility and changes in stock market volatility can be predicted by some commodity returns. However, there seems to be no discernible pattern to which commodity returns can and which commodity returns can not be used in these forecasts. This could be an interesting topic for further research.

In the hypothesis for the research question, I stated that I expected some commodities, mainly the commodities in the energy category, to be negatively impacted by stock market uncertainty. While this turned out to be true, the second part of the hypothesis, which stated that some commodities would also benefit from this uncertainty, is false. It turns out that not a single commodity is positively correlated to stock market volatility, meaning the assertion that (some) commodities are safe-havens during times of crises is incorrect. The hypothesis was also incorrect in the sense that it was stated that the correlation coefficients between both variables would be strong. In fact, like mentioned earlier, not a single one is even high enough to not be considered weak.

6 Conclusion

In this paper, data was gathered and analysed to answer the following research question:

To what extent are commodity returns related to changes in stock market volatility?

Three sub-questions were also asked in an attempt to learn more about commodities and their relationship to the stock market. Based on the data, four main conclusions can be drawn. First of all, commodities can not be considered a homogenous asset class. This is concluded based on the low correlation coefficients of the various commodity returns. In fact, not a single coefficient between commodities of different categories was high enough to be considered strong, confirming the hypothesis for the second sub-question. Secondly, commodity returns can Granger-cause and can be Granger-caused by stock market volatility. Thirdly, this Granger-causality can be used to construct models which forecast commodity returns and stock market volatility better than other forecasts based on historical prices. These two findings form the answer to sub-question three and partly confirm the corresponding hypothesis. While it is indeed true that not all commodities can be used to predict changes in volatility, there seems to be no clear pattern as to which commodities can and which commodities cannot be used for those predictions. Furthermore, changes in stock market volatility are not a significant predictor for every commodity as stated by the hypothesis. Lastly, it was found that commodity returns are significantly correlated to stock market volatility.

These four findings were used to formulate the following answer to the aforementioned research question: most commodity returns are negatively, albeit weakly, correlated to changes in stock market volatility. Their relationship can be used to build models to predict either one of the two variable, with forecasts based on these models outperforming forecasts based on historical averages. However, not every commodity's returns can be used to predict (or be predicted by) changes in stock market volatility. Why some commodities seem to be more heavily linked to the stock market than others, is an interesting premise for further research. This answer disproves the main hypothesis, which stated that the correlation between both variables would be strong and that it would be positive for at least some commodities as well. It seems that the common idea that commodities are a way of 'going long on fear' is overstated if not completely incorrect.

References

Arnold, S., & Auer, B. R. (2015). What do scientists know about inflation hedging?. *The North American Journal of Economics and Finance, 34*, 187-214.

Banerjee, J. (2013). Origins of Growing Money. *India: Forbes India Magazine.*

Bird, P. J. (1984). Commodities as a hedge against inflation. *Applied Economics, 16(6),* 855-867.

Bodie, Z. (1976). Common stocks as a hedge against inflation. *The journal of finance, 31(2),* 459-470.

Brenner, M., & Galai, D. (1989). New financial instruments for hedge changes in volatility. *Financial Analysts Journal, 45(4),* 61-65.

CBOE (2019). “Whitepaper: Cboe Volatility Index” . *CBOE.com*

Chen, J. (2021). Volatility. Investopedia. Retrieved from https://www.investopedia.com/terms/v/volatility.asp

CME Group. (n.d.). Understanding Seasonality in Grains. Retrieved from https://www.cmegroup.com/education/courses/introduction-to-agriculture/grains-oilseeds/understanding-seasonality-in-grains.html#:~:text=With%20corn%2C%20the%20most%20pronounced,summer%20into%20the%20harvest%20season.

Connolly, R., Stivers, C., & Sun, L. (2005). Stock market uncertainty and the stock-bond return relation. *Journal of Financial and Quantitative Analysis*, 161-194.

Corporate Finance Institute. (n.d.). Hard vs Soft Commodities. Retrieved from https://corporatefinanceinstitute.com/resources/knowledge/trading-investing/hard-vs-soft-commodities/

Corporate Finance Institute. (n.d.). Volatility. Retrieved from https://corporatefinanceinstitute.com/resources/knowledge/trading-investing/volatility-vol/

Corporate Finance Institute. (n.d.) What is a store of value? Retrieved from: https://corporatefinanceinstitute.com/resources/knowledge/valuation/store-of-value/#:~:text=A%20store%20of%20value%20is,time%20but%20doesn't%20depreciate.

Creti, A., Joëts, M., & Mignon, V. (2013). On the links between stock and commodity markets' volatility. *Energy Economics, 37,* 16-28.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association, 74(*366a), 427-431..

Fernando, J. (2021). Correlation Coefficient. Retrieved from https://www.investopedia.com/terms/c/correlationcoefficient.asp#:~:text=The%20correlation%20coefficient%20is%20a,error%20in%20the%20correlation%20measurement.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: journal of the Econometric Society,* 424-438.

Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of political economy, 91(2)*, 228-248.

Kang, W., Ratti, R. A., & Vespignani, J. (2020). Global commodity prices and global stock market volatility shocks: Effects across countries. *Journal of Asian Economics, 71,* 101249.

Kennon, J. (2020). What is a commodity? The Balance. Retrieved from https://www.thebalance.com/what-are-commodities-356089

Liang, C., Ma, F., Li, Z., & Li, Y. (2020). Which types of commodity price information are more useful for predicting US stock market volatility?. *Economic Modelling, 93*, 642-650.

Lintner, J. (1975). Inflation and security returns. *The journal of finance, 30*(2), 259-280.

Mankiw, N. G. (2020). *Essentials of economics.* Cengage learning.

McLean, R. D., & Pontiff, J. (2016). Does academic research destroy stock return predictability?. *The Journal of Finance, 71*(1), 5-32.

Mishra, P. K., Das, J. R., & Mishra, S. K. (2010). Gold price volatility and stock market returns in India. *American Journal of Scientific Research, 9*(9), 47-55

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

Penn State Eberly College of Science. (n.d.). 1.9 – Hypothesis Test for the Population Correlation Coefficient. Retrieved from https://online.stat.psu.edu/stat501/lesson/1/1.9

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

Salisu, A. A., Isah, K. O., & Raheem, I. D. (2019). Testing the predictability of commodity prices in stock returns of G7 countries: Evidence from a new approach. *Resources Policy, 64,* 101520.

Sarwar, G., & Khan, W. (2017). The effect of US stock market uncertainty on emerging market returns. *Emerging Markets Finance and Trade, 53*(8), 1796-1811.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 1-48.

Smith, G. (2001). The price of gold and stock price indices for the United States. *The World Gold Council, 8*(1), 1-16.

Stringham, E. (2003). The extralegal development of securities trading in seventeenth-century Amsterdam. *The Quarterly Review of Economics and Finance, 43*(2), 321-344.

Taylor, R. (1990). Interpretation of the correlation coefficient: a basic review. *Journal of diagnostic medical sonography, 6*(1), 35-39.

Terrel, E., & Vu, A. (2017). Library of Congress business history: Dow Jones Industrial Average first published. Retrieved from: https://www.loc.gov/rr/business/businesshistory/May/djia.html#overview

U.S. Department of Agriculture. (2014). USDA Announces Funding, Issues Federal Order to Combat PEDv. Retrieved from https://www.usda.gov/media/press-releases/2014/06/05/usda-announces-funding-issues-federal-order-combat-pedv

Vo, M. (2011). Oil and stock market volatility: A multivariate stochastic volatility perspective. *Energy Economics, 33*(5), 956-965.

Appendix

Table 1

Descriptive Statistics

Table 1 gives an overview of all the commodities included in this paper. In the first column, the commodity is named. In the second column, the exchange on which it is traded is named. Data was gathered from five different exchanges: New York Mercantile exchange (NYMEX), Commodity Exchange Inc. (COMEX), New York Board of Trade (NYBOT), Chicago Board of Trade (CBOT) and the Chicago Mercantile Exchange (CME). The third column gives the start date for the price data for each commodity. The last column states the mount of data points were available for each time series.

Commodity	**Exchange**	**Start date**	**N**
Energy commodities			
Crude Oil	NYMEX	1-9-2000	4977
Heating Oil	NYMEX	1-9-2000	4979
Natural Gas	NYMEX	1-9-2000	4980
RBOB Gasoline	NYMEX	1-11-2000	4938
Metal commodities			
Copper	COMEX	1-9-2000	4978
Gold	COMEX	1-9-2000	4970
Platinum	NYMEX	1-9-2000	4279
Silver	COMEX	1-9-2000	4972
Agricultural commodities			
Corn	CBOT	1-9-2000	4937
Cotton	NYBOT	1-9-2000	4968
Lean Hogs	CME	1-4-2002	4597
Soybean Oil	CBOT	1-9-2000	4840
Sugar	NYBOT	1-9-2000	4969
Commodity indices			
S&P GSCI	CME	1-4-2006	3502

Table 2

Correlation between the different commodities

Table 2 gives an overview of each commodity's correlation to every other commodity. The significance of each correlation coefficient is indicated using * (10%), ** (5%) or *** (1%).

Commodity	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Crude Oil	1.000						
(2) Heating Oil	-0.032**	1.000					
(3) Nat. Gas	0.106***	0.054***	1.000				
(4) RBOB Gasoline	0.454***	0.011	0.186***	1.000			
(5) Copper	0.191***	0.005	0.075***	0.250***	1.000		
(6) Gold	0.107***	0.041***	0.080***	0.129***	0.275***	1.000	
(7) Platinum	0.161***	0.036***	0.056***	0.213***	0.336***	0.458***	1.000
(8) Silver	0.159***	0.027**	0.089***	0.203***	0.394***	0.652***	0.501***
(9) Corn	0.116***	0.017	0.092***	0.131***	0.191***	0.143***	0.143***
(10) Cotton	0.092***	0.012	0.049***	0.137***	0.187**	0.082***	0.120***
(11) Lean Hogs	-0.18	-0.005	0.015	0.019*	0.036**	0.013	0.050***
(12) Soybean Oil	0.177***	0.010	0.010***	0.216***	0.284***	0.180***	0.213***
(13) Sugar	0.135***	0.012	0.069***	0.156***	0.183***	0.112***	0.153***
(14) S&P GSCI	0.772***	0.024**	0.024***	0.662***	0.465***	0.266***	0.354***

Commodity	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Crude Oil							
(2) Heating Oil							
(3) Nat. Gas							
(4) RBOB Gasoline							
(5) Copper							
(6) Gold							
(7) Platinum							
(8) Silver	1.000						
(9) Corn	0.157***	1.000					
(10) Cotton	0.128***	0.173***	1.000				
(11) Lean Hogs	0.030**	0.027**	0.031***	1.000			
(12) Soybean Oil	0.220***	0.408***	0.220***	0.021*	1.000		
(13) Sugar	0.169***	0.172***	0.149***	0.033**	0.179***	1.000	
(14) S&P GSCI	0.374***	0.305***	0.250***	0.067***	0.462***	0.292***	1.000

Table 3

Correlation between the different commodity categories

Table 3 gives an overview of the correlation of the average returns of each commodity category (see Table 1). The significance of each correlation coefficient is indicated using * (10%), ** (5%) or *** (1%).

Commodity Category	(1)	(2)	(3)
(1) Energy	1.000		
(2) Metals	0.267***	1.000	
(3) Agriculture	0.221***	0.314***	1.000

Table 4

Results of the Dickey-Fuller tests

Table 4 shows the results of the DF test with the following hypothesis:

$$\Delta y_t = a_0 + a_1 y_{t-1} + e_t$$

H_0 : The time series is non-stationary ($a_1 = 0$)

H_a : The time series is stationary (a_1 is significantly different from zero)

The fourth column shows the p-value at a 5% significance level.

Commodity	**Coefficient**	**T-statistic**	**P-value**
Crude Oil	-0.963	-67.99	0
Heating Oil	-0.789	-56.95	0
Natural Gas	-0.796	-57.36	0
RBO Gasoline	-0.815	-58.24	0
Energy Commodity Average	-0.800	-58.64	0
Copper	-0.871	-61.95	0
Gold	-0.822	-58.85	0
Platinum	-0.928	-60.84	0
Silver	-0.875	-62.13	0
Metal Commodity Average	-0.815	-58.55	0
Corn	-0.835	-59.45	0
Cotton	-0.806	-57.88	0
Lean Hogs	-0.881	-60.17	0
Soybean Oil	-0.851	-59.89	0
Sugar	-0.815	-58.47	0
Agricultural Commodity Average	-0.826	-59.24	0
S&P GSCI	-0.893	-53.13	0
Volatility Index	-0.908	-65.20	0

Table 5

Vector Autoregressive models of the energy commodities

Table 5 shows the specifications for the VAR[1] models of the energy commodities. The model consists of the following two equations:

(1) $$r_{i,t} = \beta_{1,1} r_{i,t-1} + \beta_{1,2} \Delta V_{t-1} + e_{1,t}$$

(2) $$\Delta V_t = \beta_{2,1} r_{i,t-1} + \beta_{2,2} \Delta V_{t-1} + e_{2,t}$$

The significance of each coefficient is indicated using * (10%), ** (5%) or *** (1%). Standard errors are in brackets. The last column gives the VAR[1] model of the average energy commodities return, not the average of the individual VAR[1] models.

Commodity	Crude Oil	Heating Oil	Natural Gas	RBOB Gasoline	Energy Average
Equation 1					
$\beta_{1,1}$	0.031***	0.211***	0.204***	0.177***	0.196***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$\beta_{1,2}$	-0.026***	-0.004	-0.004	-0.017***	-0.009**
	(0.009)	(0.004)	(0.006)	(0.005)	(0.004)
R-squared	0.003	0.045	0.042	0.036	0.042
Equation 2					
$B_{2,1}$	0.056**	-0.355***	0.008	0.064*	0.004
	(0.024)	(0.047)	(0.031)	(0.038)	(0.052)
$B_{2,2}$	0.099***	0.094***	0.096***	0.099***	0.093***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
R-squared	0.010	0.020	0.009	0.010	0.009

Table 6

Vector Autoregressive models of the metal commodities

Table 6 shows the specifications for the VAR[1] models of the metal commodities. The model consists of the following two equations:

(1) $$r_{i,t} = \beta_{1,1} r_{i,t-1} + \beta_{1,2} \Delta V_{t-1} + e_{1,t}$$

(2) $$\Delta V_t = \beta_{2,1} r_{i,t-1} + \beta_{2,2} \Delta V_{t-1} + e_{2,t}$$

The significance of each coefficient is indicated using * (10%), ** (5%) or *** (1%). Standard errors are in brackets. The last column gives the VAR[1] model of the average metal commodities return, not the average of the individual VAR[1] models.

Commodity	Copper	Gold	Platinum	Silver	Metal Average
Equation 1					
$\beta_{1,1}$	0.108***	0.179***	0.060***	0.115***	0.169***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.014)
$\beta_{1,2}$	-0.018***	-0.006***	-0.015***	-0.021***	-0.013***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.003)
R-squared	0.022	0.034	0.010	0.021	0.039
Equation 2					
$\beta_{2,1}$	0.180***	0.109	0.075	0.100**	0.202**
	(0.062)	(0.089)	(0.068)	(0.048)	(0.080)
$\beta_{2,2}$	0.106***	0.096***	0.098***	0.099***	0.102***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.014)
R-squared	0.011	0.009	0.009	0.010	0.010

Table 7

Vector Autoregressive models of the agricultural commodities & the commodity index

Table 6 shows the specifications for the VAR[1] models of the agricultural commodities and the commodity index. The model consists of the following two equations:

(1) $$r_{i,t} = \beta_{1,1} r_{i,t-1} + \beta_{1,2} \Delta V_{t-1} + e_{1,t}$$

(2) $$\Delta V_t = \beta_{2,1} r_{i,t-1} + \beta_{2,2} \Delta V_{t-1} + e_{2,t}$$

The significance of each coefficient is indicated using * (10%), ** (5%) or *** (1%). Standard errors are in brackets. The second-to-last column gives the VAR[1] model of the average agricultural commodities return, not the average of the individual VAR[1] models.

Commodity	Corn	Cotton	Lean Hogs	Soybean Oil
Equation 1				
$\beta_{1,1}$	0.164***	0.188***	0.119***	0.137***
	(0.014)	(0.014)	(0.015)	(0.014)
$\beta_{1,2}$	-0.005	-0.012***	0.000	-0.016***
	(0.004)	(0.004)	(0.001)	(0.003)
R-squared	0.028	0.040	0.014	0.027
Equation 2				
$\beta_{2,1}$	-0.004	0.047	0.117***	0.117*
	(0.055)	(0.052)	(0.040)	(0.068)
$\beta_{2,2}$	0.093***	0.097***	0.096***	0.098***
	(0.014)	(0.014)	(0.015)	(0.014)
R-squared	0.009	0.009	0.011	0.010

Commodity	Sugar	Agricultural Average	S&P GSCI
Equation 1			
$\beta_{1,1}$	0.184***	0.167***	0.099***
	(0.014)	(0.014)	(0.018)
$\beta_{1,2}$	-0.002	-0.007***	-0.005
	(0.004)	(0.002)	(0.004)
R-squared	0.034	0.033	0.013
Equation 2			
$\beta_{2,1}$	0.135***	0.292***	0.203**
	(0.048)	(0.092)	(0.088)
$\beta_{2,2}$	0.100***	0.104***	0.113***
	(0.014)	(0.014)	(0.018)
R-squared	0.011	0.011	0.012

Table 8

An overview of the Granger-causality present in the observed time-series

Table 8 gives an overview of whether or not each commodity is Granger-caused by changes in stock market volatility and whether or not each commodity Granger-causes changes in stock market volatility. The Granger-causality is based on coefficients $\beta_{1,2}$ and $\beta_{2,1}$ found in Table 5, Table 6 and Table 7. In this paper, the 5% (**) significance threshold is used to determine the existence of Granger-causality.

Commodity	**Granger-caused by changes in stock market volatility**	**Granger-causes changes in stock market volatility**
Crude Oil	Yes	Yes
Heating Oil	No	Yes
Natural Gas	No	No
RBOB Gasoline	Yes	No
Energy Commodities Average	Yes	No
Copper	Yes	Yes
Gold	Yes	No
Platinum	Yes	No
Silver	Yes	Yes
Metal Commodities Average	Yes	Yes
Corn	No	No
Cotton	Yes	No
Lean Hogs	No	Yes
Soybean Oil	Yes	No
Sugar	No	Yes
Agricultural Commodities Average	Yes	Yes
S&P GSCI	No	Yes

Table 9

Mean squared errors for the commodity returns forecast

Table 9 gives an overview of the mean squared error (MSE) of the forecasts of various commodity returns. The first column shows which commodity's returns are being forecasted. The last column shows the difference between the MSE of the forecasts based on the VAR[1] models and the forecast based on the simple moving average (SMA). MSE is multiplied x 1000 to make it easier to read. If the value in the last column is negative, the forecast based on the VAR[1] model is better than the SMA forecast.

Commodity	**MSE VAR Forecast (x 10^{-3})**	**MSE SMA Forecast (x 10^{-3})**	**ΔMSE (x 10^{-3})**
Crude Oil	1.308	1.447	- 0.139
RBOB Gasoline	1.179	1.240	- 0.061
Energy Average	0.951	0.948	0.003
Copper	0.114	0.116	- 0.002
Gold	0.074	0.080	- 0.006
Platinum	0.406	0.417	- 0.011
Silver	0.319	0.349	- 0.030
Metal Average	0.123	0.134	- 0.011
Cotton	0.179	0.182	- 0.003
Soybean Oil	0.114	0.123	- 0.009
Agricultural Average	0.092	0.101	- 0.009

Table 10

Mean squared errors for the stock market volatility forecast

Table 10 gives an overview of the mean squared error (MSE) of the forecast of changes in stock market volatility, using various commodities. The first column shows which commodity was used to perform the forecast. The MSE of the SMA forecast obviously remains the same, as the same variable is being forecasted each time. The last column shows the difference between the MSE of the forecasts based on the VAR[1] models and the forecast based on the simple moving average (SMA). MSE is multiplied x 1000 to make it easier to read. If the value in the last column is negative, the forecast based on the VAR[1] model is better than the SMA forecast.

Commodity	**MSE VAR Forecast (x 10^{-3})**	**MSE SMA Forecast (x 10^{-3})**	**ΔMSE (x 10^{-3})**
Crude Oil	4.166	5.030	- 0.864
Heating Oil	4.811	5.030	- 0.219
Copper	4.922	5.030	- 0.108
Silver	4.948	5.030	- 0.082
Metal Average	4.934	5.030	- 0.096
Lean Hogs	5.259	5.030	0.229
Sugar	4.932	5.030	- 0.098
Agricultural Average	5.244	5.030	0.214
S&P GSCI	4.321	5.030	- 0.709

Table 11

Correlation table of commodity returns and changes in stock market volatility

Table 11 shows the correlation coefficients for commodity returns and changes in stock market volatility. The significance of each correlation coefficient is indicated using * (10%), ** (5%) or *** (1%).

Commodity	Stock market volatility
Crude Oil	-0.128***
Heating Oil	-0.007
Natural Gas	-0.025*
RBOB Gasoline	-0.178***
Energy Commodities Average	-0.140***
Copper	-0.280***
Gold	-0.013
Platinum	-0.187***
Silver	-0.147***
Metal Commodities Average	-0.261***
Corn	-0.111***
Cotton	-0.140***
Lean Hogs	-0.046***
Soybean Oil	-0.156***
Sugar	-0.110***
Agricultural Commodities Average	-0.190***
S&P GSCI	-0.323***