MASTERARBEIT / MASTER’S THESIS

Titel der Masterarbeit / Title of the Master‘s Thesis

„Does uncertainty impact gold return volatility and its correlation with the market different than other assets?“

verfasst von / submitted by

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Abstract (English)

This paper aims to assess whether conditional gold volatility and the conditional correlation between gold and the market react significantly to exogenous shocks in market uncertainty. In order to evaluate whether gold has special financial characteristics in times of crisis, the coefficients are compared to those found using silver, copper, crude oil, the NASDAQ, and the S&P500. At first, the regression is carefully specified and the controls are justified. The data are from August 30^{th}, 2000 to January 9^{th}, 2023 and are provided at a daily frequency. The dynamic causal effects of an uncertainty shock on the conditional volatility of an asset, on the growth in conditional volatility, on the conditional correlation between an asset and the market, and on the growth in conditional correlation between an asset and the market are measured. Conditional gold return volatility is expected to increase after such an innovation, independent of the selection of the market uncertainty proxy or the way volatility is measured. There is a negative impact or no significant impact of a shock in market uncertainty on the correlation between gold and a market portfolio, depending on the selection of the uncertainty proxy and whether correlation or growth in correlation is analyzed. Hence, gold can be considered a safe haven. The volatility of no other asset is impacted less by shocks in market uncertainty. The effects on the conditional correlation between no other asset and the market are significantly less than those on the conditional correlation between gold and the market. These results emphasize the unique role of gold in times of high market uncertainty.

Abstract (Deutsch)

Das Ziel der Arbeit ist es herauszufinden, ob die bedingte Volatilität von Gold und die bedingte Korrelation zwischen Gold und dem Markt auf exogene Marktunsicherheitsschocks reagieren. Um zu evaluieren, ob Gold spezielle finanzwirtschaftliche Eigenschaften in Zeiten hoher Marktunsicherheiten besitzt, werden die Koeffizienten mit jenen verglichen, wenn Silber, Kupfer, Öl, der NASDAQ Index oder der S&P 500 Index verwendet werden. Die Herangehensweise, um die relevanten Effekte zu finden, wird aus statistischer und ökonomischer Perspektive erklärt. Die verwendeten Daten sind vom 30. August 2000 bis zum 9. Januar 2023 und sind in täglicher Frequenz verfügbar. Die dynamischen, kausalen Effekte von einem Marktunsicherheitsschock auf die bedingte Volatilität, auf das Wachstum der bedingten Volatilität, auf die bedingte Korrelation zwischen dem jeweiligen Vermögenswert und dem Marktportfolio und auf das Wachstum der bedingten Korrelation zwischen dem jeweiligen Vermögenswert und dem Marktportfolio werden gemessen. Es wird erwartet, dass die bedingte Volatilität von Gold nach einem exogenen Schock wächst, unabhängig davon, wie Marktunsicherheit quantifiziert wird oder wie Volatilität gemessen wird. Ein Marktunsicherheitsschock beeinflusst die Korrelation zwischen Gold und dem Marktportfolio gar nicht oder sogar negativ, abhängig davon, wie Marktunsicherheit quantifiziert wird und ob man die Einflüsse auf die Korrelation oder das Wachstum der Korrelation misst. Folglich kann Gold als "sicherer Hafen" eingestuft werden. Die Volatilität von keinem anderen Vermögenswert ist weniger von Innovationen in Marktunsicherheiten beeinflusst als jene von Gold. Die Effekte auf die bedingte Korrelation zwischen Gold und dem Marktportfolio sind kleiner als auf jene von jedem anderen Vermögenswert. Die Ergebnisse unterstreichen die einzigartige Rolle von Gold in Zeiten von hoher Marktunsicherheit.

Contents

1 Introduction & Motivation

We have already witnessed several crises and situations of uncertainty at the beginning of this new decade. The Covid pandemic has affected our daily lives, the decisions of policymakers, and movements in financial markets since early 2020. Russian President Vladimir Putin started a war in Eastern Europe in February 2022, just when there appeared to be a trend toward normality.

Apart from all the human tragedy, a well-known phenomenon in financial markets was detected. In times of high financial uncertainty, investors around the globe are searching for so-called safe havens. The demand for gold as an investment asset doubled when the Covid pandemic broke out in early 2020, according to the World Gold Council (2023). Generally, safe havens are defined as assets that are uncorrelated or even negatively correlated with the market in times of uncertainty, according to Baur and McDermott (2010). Hence, private and institutional investors use safe havens to diversify their portfolios. The first asset that comes to almost everyone's mind when talking about safe havens is gold. Many currencies were backed up by gold in former times. This indicates how much trust people have in gold. Hence, people tend to increase their demand for gold when they are in situations of high uncertainty, as we have seen in the example before. The aim of this paper is to answer whether this reputation is justified.

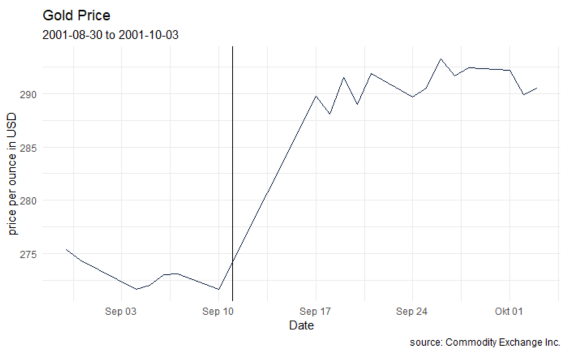


Figure 1

Figure 2

Looking at certain events, the reaction of the gold price to unexpected market-wide shocks is different than the reaction of other assets. The gold price increased sharply after the terrorist attacks from September 2001, while the S&P 500 deteriorated, as figures 1 and 2 indicate. This example is chosen since 9/11 was an unexpected event. The S&P500, which covers a wide range of different US corporations, moves in the opposite direction of the gold prices during that time of high market uncertainty. Certainly, one example is not enough to draw general conclusions. However, it should motivate the question of this paper: Is there a more negative correlation between gold and the market during times of high uncertainty? Furthermore, it should be answered whether the volatility of gold is less affected by uncertainty shocks than the volatility of other assets.

The approach is to define uncertainty shock proxies first. The CBOE volatility index and average credit spreads are taken. GARCH-based volatility and volatility based on an approach by Garman and Klass (1980) is calculated. Next, leads of differenced conditional volatilities are regressed on the market uncertainty proxy and controls. Furthermore, impulse response functions of a transformed vector autoregression are calculated. The results are interpreted from an economic and financial point of view. It is assessed whether gold behaves differently than other assets. The same regressions are performed using the dynamic conditional correlation of an asset with a market portfolio as the explained variable. Last, it is shown that the weights of gold in a minimum variance portfolio consisting of gold and another asset change in times of higher uncertainty as predicted by the findings of this paper.

The main takeaways are that gold has special characteristics. The conditional volatility of gold increases less than that of the SP500, the NASDAQ, silver or oil in times of higher market uncertainty. It is not always possible to reject the null hypothesis that the impacts are the same when copper is considered. However, there is no other asset whose volatility is impacted significantly less, independent of the selection of the market uncertainty shock. Moreover, gold is one of the only asset whose correlation with the market is negatively impacted by an increase in market uncertainty. The correlation of most other assets with the market is unaffected or positively impacted by such shocks. Because of these findings, the minimum variance portfolio of gold and the SP500 or the NASDAQ has higher gold weights in times of high market uncertainty.

2 Literature Review

The research on gold has been increasing since the 1960s when the constraints on gold price fluctuation were canceled as shown by O'Connor et al. (2015). They show that more research on the financial characteristics of gold is conducted during a financial or geopolitical crisis. Additionally, they demonstrate that the total number of articles published about gold as an investment asset doubled during the Great Recession compared to the level in 2004.

Substantial research has been conducted on whether gold fulfills its role as a hedge or safe haven. According to Lucey and Baur (2010), a hedge is defined as "*an asset that is uncorrelated or negatively correlated with another asset or portfolio on average*". Chua et al. (1990) find that the beta of gold is comparably low for the time period between 1971 and 1988. Moreover, they cannot reject the null hypothesis that the beta is zero, thereby confirming the role of gold as a hedge. More recent work by Emmrich and McGroarty (2013) underlines that gold reduces the volatility of several investigated portfolios. An active field of research is the hedging ability of gold for currency risk. Reboredo (2013) conclude that gold is a dollar hedge for eight currencies.

The role of gold as a safe haven has also been investigated. According to Baur and McDermott (2010), the definition is as follows.

> *A strong (weak) safe haven is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio in certain periods only, e.g. in times*

of falling stock markets.

Lucey and Baur (2010) find that gold fulfills its role as a safe haven for stocks but not for bonds. Baur and McDermott (2010) also test the hypothesis that gold is a safe haven. Their results are that the negative correlation is the highest for extreme shocks for which the probability of occurrence is less than 1 %. Moreover, they also conclude that gold is a strong safe haven in most developed economies like the US or the Eurozone. Hence, its relationship with the market is negative. However, for weaker economies, gold is uncorrelated with the market at best in times of crisis. Ciner et al. (2013) construct a dynamic conditional correlation model for gold and its relation to the US dollar and the British pound. For both currencies, gold shows characteristics of a safe haven. These papers have already laid the ground for our understanding of how gold is related to other assets at certain times. The difference to my research is that most papers are solely investigating the relationship between gold returns and market returns or returns of other assets. This paper also tests whether the impacts on the correlation of other assets with the market portfolio are significantly different from the effects on the correlation of gold with the market portfolio. Hence, the aim is to find out whether the role of gold is unique.

This paper also measures the impacts of uncertainty shocks on conditional asset volatility. Most research focused on the drivers and determinants of volatility. For example, Batten et al. (2010) find that stock returns, dividend yields, money supply, and CPI in the US are important drivers for gold volatility. They conclude that the drivers of the volatility of other precious metals like silver, platinum, and palladium are different. Hammoudeh et al. (2010) find that monetary shocks have long-run effects on the volatility of silver and gold. Cai et al. (2001) consider intraday gold volatility and find that the volatility is higher at the beginning and end of the trading day. Moreover, they determine which macroeconomic news announcements are most impactful for gold volatility. They find that only four factors significantly impact gold volatility, which are employment, GDP, CPI, and personal income. Byers and Peel (2001) conclude that gold volatility has a particularly long memory, in the sense that the impacts of volatility shocks are long-lived. Those studies are close to the topic of the work at hand. The difference is that this study is not specifically concerned with what drives gold volatility but with whether its volatility is impacted differently by uncertainty shocks than the volatility of other assets. Hence, both the immediate impacts on the growth of gold volatility and the long-term effects on gold volatility are measured.

As a result, the paper wants to add to the current state of knowledge by assessing the characteristics of gold by comparing its reaction in times of high market uncertainty to the response of other assets.

3 Data Description & Transformations

This section describes which data sources are used and how the time series are transformed. Generally, the frequency of all observations is daily. When the option is available, closing prices are used, which is the last observation of each day. The time interval is between August 30, 2000, and January 9, 2023. When information for one variable on a certain day is not available, the whole day is dropped from the data frame. The final data frame consisted of 5584 observations. The justification for the usage of data from mid-2000 to the beginning of 2023 is that the bigger the time series and the higher the variation of the data, the smaller the estimated variance of the coefficient estimates. A smaller sample size can therefore lead to different results because some coefficients are not significant anymore.

The economic reason for using daily data is that this paper aims to find the impacts of exogenous changes in uncertainty on asset return volatilities over time. Hence, the higher the frequency, the more precise the evolvement of the impacts over time.

3.1 Gold

The data for the prices of gold are provided by Yahoo Finance which uses information published by the Commodity Exchange Inc. The COMEX is one of the most important commodity future exchanges in the world. The values indicate the prices for one-month futures for one ounce in US-Dollar. Figure 3 shows the gold price over time. We can see that the price in 2023 is almost seven times the value from 2000. In 2012, the gold price peaked and fell afterward. This level was reached in 2020 again.

We need gold return volatility for our analysis. Hence, logarithmic returns are calculated using the formula $r_t = ln(P_t) - ln(P_{t-1})$. The time series is indicated in the lower half of figure 4. We can see typical characteristics of an asset return time series. The mean value is zero or slightly above zero. Moreover, it can be observed that the returns are unlikely to be independent. High absolute returns are typically followed by further high absolute returns. Returns of frequently traded assets are usually serially uncorrelated. However, this does not mean that returns do not depend on each other. For example, the absolute returns from 2008 and 2009 exceed those from 2018 to 2019 on average.

We need to obtain conditional volatilities for the regressions in the sections below. The approach is to specify a mean model for returns. It is tested whether there are ARCH effects. If this is the case, the mean and volatility equations are jointly estimated. Model diagnostics help us to determine whether the specification is appropriate. Adjustments and refinements are made if necessary. When an appropriate model is found, the volatility is saved and used in the regressions below. This approach to building a proper volatility model is proposed by Tsay (2005).

The autocorrelations and partial autocorrelations of logarithmic gold returns are usually low and not significantly different from zero. This is not a surprise and a typical characteristic of financial time series, as outlined before. Hence, an ARIMA(0,0,0) is an appropriate mean specification. This intuition is strengthened by the Bayesian and Akaike information criterion, which is minimized by an ARIMA(0,0,0) model. As a result, the residuals of the estimation are the demeaned returns. The ACFs and PACFs of squared gold returns are not independent. Positive and statistically significant correlations can be found. Two different Arch tests are performed to check whether a process is stationary. One is based on a Portmanteau Q test and the other on a Lagrange Multipliers test. Both indicate that the null hypothesis of homoscedasticity can be rejected. Hence, we specify a mean and a volatility model in the next step. The initial guess is an ARMA(0,0)-sGARCH(1,1)-norm model. Bollerslev (1986) introduced GARCH models first. Norm stands for normal distribution and indicates the density of innovations. In order to evaluate whether the chosen specification is correct, dynamic properties of $\hat{z}$ and $\hat{z}^2$ are checked. Note that $\hat{z}$ indicates standardized residuals, such that

$$\hat{z}_t = \frac{\hat{u}_t}{\hat{\sigma}_t}$$

$\hat{u}_t$ are the residuals of the mean model. Then, a Ljung-Box Test on standardized residuals and squared standardized residuals for different numbers of lags is performed. The null hypothesis of this test is that there is no serial correlation.

$$H_0 : \rho_1 = \rho_2 = \rho_3 = ... = 0$$

Independent of the number of lags, the test fails to reject. Furthermore, we also consider a Lagrange Multiplier test to find out whether lagged residuals have explanatory power for current residuals. The null hypothesis is that there is no explanatory power and that the time series is white noise, which cannot be rejected. However, the distributional assumption seems to be incorrect. The Pearson Goodness of fit test compares the distribution of the residuals with the theoretical distribution. The null hypothesis is that they are the same, which is rejected. Klar et al. (2012) show that GARCH estimates are still consistent when the incorrect innovation distribution is chosen. However, the loss of efficiency can be as high as 84 %, according to Engle and González-Rivera (1991). Hence, alternative distributions are applied. According to the Pearson goodness of fit test, a Johnson SU distribution is preferred. An ARMA(0,0)-sGARCH(1,1)-jsu model fulfills that the Ljung Box tests for standardized residuals and squared standardized residuals are not rejected and that the Pearson Goodness of fit test cannot reject that the distribution of the residuals and the theoretical distribution are identical.

Moreover, an ARMA(0,0)-sGARCH(1,1)-jsu model is then compared with further variance specifications. It can be stated that the BIC is minimized with the suggested specification besides the fact that other specifications violate distributional or dynamic properties of $\hat{z}$. The plotted standardized residuals look like a white noise process with zero mean, constant variance, and zero autocorrelation. The autocorrelation functions of standardized residuals and squared standardized residuals indicate what has been tested by the Ljung Box test. None of the correlations for lags bigger than zero is statistically different from zero. The plots can be found in the appendix. Hence, the conditional volatility is calculated using an ARMA(0,0)-sGARCH(1,1)-jsu model. Figure 4 displays the results.

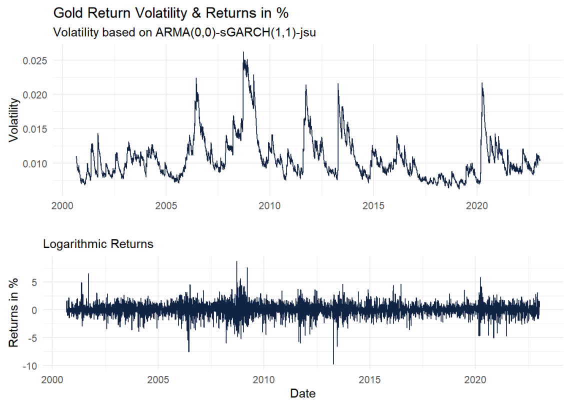


Figure 3 Figure 4

We can see that there are times of higher and lower volatility. Spikes occurred in 2006, 2008, 2013, and 2020. In the following subsections, it is tested whether it is a coincidence that high volatilities are detected when there is high market uncertainty. The Great Recession lasted from 2007 to 2009. Gold volatility reached its highest point of our sample size in 2008. Moreover, in early 2020, Covid-19 spread across the globe. Gold volatility increased at that time.

3.2 Silver

Yahoo Finance provides the data for the prices of silver. The website draws information from the COMEX (Commodity Exchange Inc.). The values indicate the price for silver futures for one ounce in US-Dollar. Figure 5 depicts silver prices from August 2000 to January 2023. The price in 2023 is almost five times the price from 2000 but is approximately 50 % lower than in April 2011. Silver prices almost doubled at the beginning of the global spread of the coronavirus compared to the value at the end of 2019. However, they still remain at a lower level than in April 2011.

This paper aims to compare the impact of market uncertainty on volatility of different assets as the motivation pointed out. Gold can be compared to countless other investment opportunities. Hence, we justify those that are selected. Silver, palladium, platinum, and gold are the four precious metals, which is why they share several chemical properties. The summary statistics in the appendix indicated that the correlation between gold and silver returns is 0.7835. This is the highest between gold and any assets considered in this paper. The economic usage of gold and silver is similar, as described by Baur and McDermott (2010). Both are used in jewelry and as investment assets. However, gold has limited usage for industrial purposes. On the other hand, silver is an essential part of the industrial economy. It is used for photography, solar energy, or medical products. Similarities between gold and silver are that the short-term supply is relatively fixed and price independent. However, higher prices lead to more investments in mines in the long run. This causes the supply of precious metals to increase, according to Selvanathan and Selvanathan (1999).

The lower part of figure 6 shows a plot of the time series of log returns of silver. High absolute returns are typically followed by further high absolute returns. This is similar to our previous findings. Silver returns are serially uncorrelated but not independent. An ARIMA(0,0,0) specification is chosen as the mean model, based on the suggestion of the BIC. As there are ARCH effects, an ARMA(0,0)-sGARCH(1,1)-norm model is tried as the mean-variance model at first. However, the Ljung Box test on squared standardized residuals indicates that this model does not capture all the dynamics in the residuals. The null hypothesis of no serial correlation cannot be rejected independent of the standard GARCH lag order. Hence, different types of GARCH models with different lag orders are tried. Unlike before, it was not possible to find a model that fulfills both dynamic and distributional properties. Hence, we had to decide between an ARMA(0,0)-gjrGARCH(2,2)-snorm model or an ARMA(0,0)-csGARCH(2,2)-nig. The first one fulfills all dynamic properties, but the innovation distribution assumption is incorrect. This type of GARCH model was first proposed by Glosten et al. (1993). This specification has the lowest BIC of all model specifications that fulfill the criterion of no serial correlation of standardized and squared standardized residuals. When we use the ARMA(0,0)-csGARCH(2,2)-nig model specification, the Adjusted Pearson Goodness-of-Fit Test does not reject the null hypothesis that the theoretical and empirical distributions are the same. However, the Ljung-Box Test on standardized squared residuals rejects the null hypothesis of no serial correlation at the 1 % significance level. Hence, it is decided to choose an ARMA(0,0)-gjrGARCH(2,2)-snorm model. As previously pointed out, the estimates are consistent. The standardized residuals are white noise. No dynamics are left.

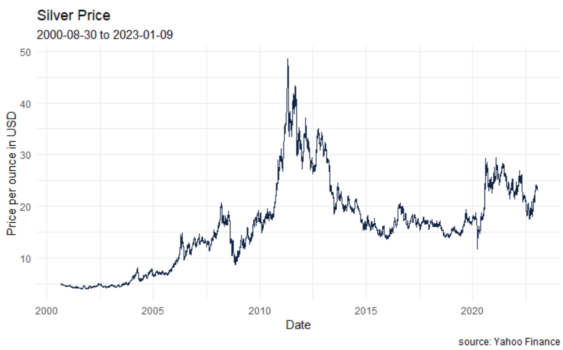


Figure 5

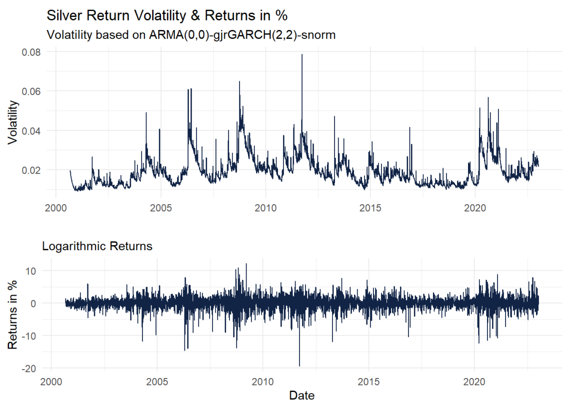


Figure 6

The time periods of high conditional silver volatility roughly coincide with those of gold. Conditional volatility tends to increase in times of higher absolute logarithmic returns.

3.3 Copper

The characteristics of gold are compared to those of copper in this paper. The economic reasoning is that copper and gold are both metals. However, copper is not a precious metal and has high industrial usage. Hence, we are interested to see whether industrially used metals react to exogenous uncertainty shocks differently. Yahoo Finance provides the data. The company draws its information once again from COMEX. The values indicate the price for futures for one pound in US-Dollar. Figure 7 shows how the price of copper evolved. Today's price is roughly four times the value from 2000. Hence, the increase is less than the price increase of gold. Moreover, we can see that the price of copper decreased sharply during the Great Recession but recovered. Figure 8 displays that the copper price fell by up to 11.69 % in October 2010. Such sharp declines are not found for gold prices. The chosen mean model for copper is an ARIMA(0,0,1) model. ARCH effects are found, and the first try of a mean-variance model specification is an ARMA(0,1)-sGARCH(1,1)-norm model. However, tests of the distributional and dynamic properties of $\hat{z}$ indicate that we need to make adjustments. Hence, an ARMA(0,1)-csGARCH(1,2)-sstd model is chosen as it fulfills the properties required. CsGARCH stands for component standard GARCH and was proposed by Ding and Granger (1996). Sstd is a skewed student t distribution. Moreover, the BIC is comparably small for this model specification, and the AIC is minimized.

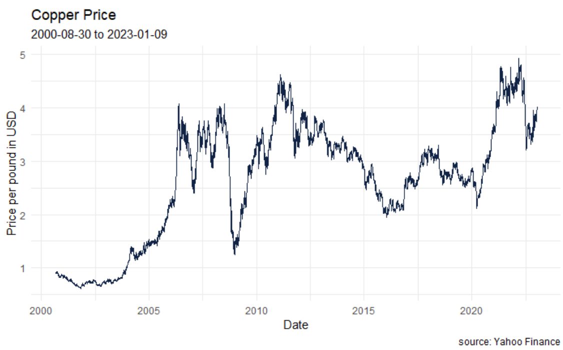


Figure 7

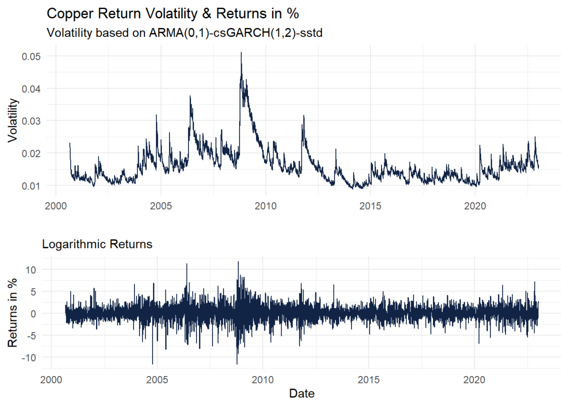


Figure 8

The conditional volatility of copper was higher during the Great Recession than at the beginning of the global Covid-19 crisis. The increase in gold and silver volatility was sharper in early 2020.

3.4 Crude Oil

Yahoo Finance makes the data used in this subsection available. The company draws information from the NYMEX (New York Mercantile Exchange). The values indicate the price for one-month futures for one barrel of crude oil in US-Dollar. The economic reason for the analysis of oil in this paper is that it is a non-metal natural resource with immense industrial and economic importance. The crude oil price decreased sharply during the Great Recession from 145 USD to around 75 USD. A similar sharp decrease occurred at the beginning of the covid crisis. The price in early 2023 is approximately twice as high as in 2000.

The ACF and PACF for crude oil suggest an ARMA(0,0) mean model. Different variance models are tried, as ARCH effects are found. An ARMA(0,0)-csGARCH(1,1)-sstd fulfills the dynamic and distributional properties required.

Figure 9

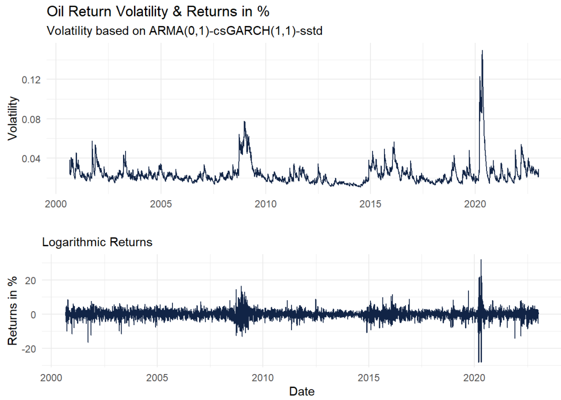


Figure 10

A cluster of high volatility in early 2020 is detected, which exceeds the volatility during the financial crisis. Oil volatility stands out during the covid crisis compared to the volatility of the metals.

3.5 NASDAQ

The data are loaded from the Yahoo Finance website, which pulls their information directly from NASDAQ Global Indexed Data Service. The NASDAQ Composite contains more than 3000 companies that mainly provide information technology services. The NASDAQ is analyzed to find out whether the reaction of the volatility of gold is different from the volatility of an index containing tech shares. The index value in early 2023 is approximately 2.5 times that of 2000. The NASDAQ has been suffering from a downward trend since early 2022. The index value was 16.057 on November 19, 2021, and was 10.635 on January 9, 2023.

As there are ARCH effects, an ARMA(1,1)-gjrGARCH(2,1)-sged model is chosen. This model fulfills all properties required. The distributional assumption is correct according to the Adjusted Pearson Goodness-of-Fit Test. Moreover, there is no serial correlation in standardized and squared standardized residuals. The Ljung Box test fails to reject the null hypothesis at the 1 % significance level.

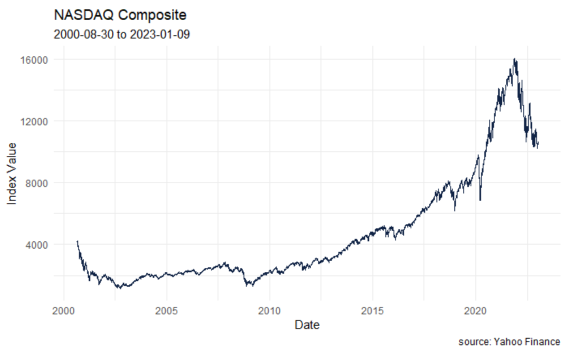


Figure 11

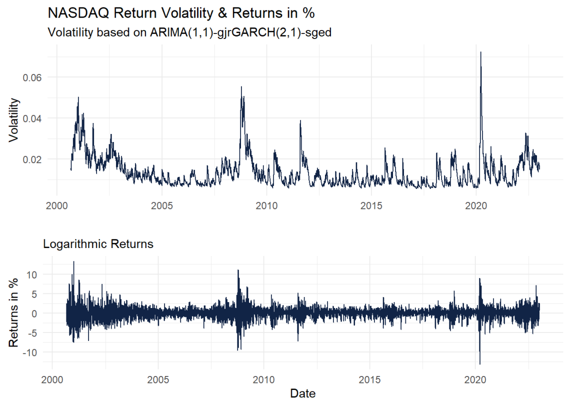


Figure 12

The volatility of the NASDAQ peaked during the Covid crisis and the Great Recession. In contrast to other assets, we can also see a period of high volatility in 2000. This is triggered by the repercussions of the DotCom bubble which specifically impacted tech shares.

3.6 S&P 500

Yahoo Finance provides the data for the S&P500. This index contains shares of the 500 biggest US companies listed on stock exchanges. The difference to the NASDAQ is that shares are from across all industries. This index is analyzed as we are interested in how the volatility of gold is impacted differently than an index representing the highest-valued US firms. It is commonly used as the market portfolio in financial econometrics literature. The index value today is 2.5 times that of 2000. Sharp increases occurred during the Great Recession and at the beginning of the Covid crisis.

The BIC chooses an ARMA(0,1) model as the mean model. Since there are ARCH effects, an ARMA(0,1)-gjrGARCH(2,1)-sged is selected. Tests show no serial correlation in $\hat{z}$ and $\hat{z}^2$. The distributional assumption is also correct.

Figure 13

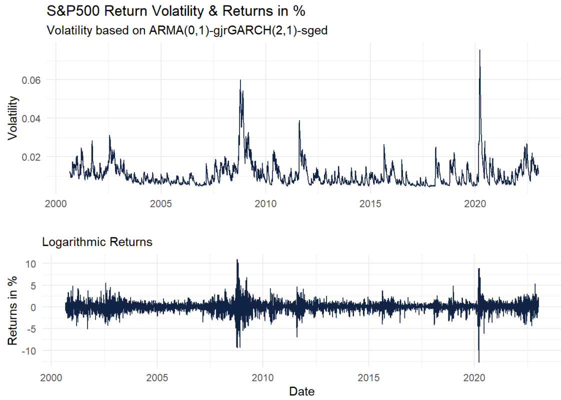


Figure 14

There is typical volatility clustering in SP500 returns. Observations of low volatility are typically followed by further observations of low volatility.

3.7 Volatility Index

We have obtained all conditional volatilities that are necessary for the regressions below in the previous subsection. The goal of this work is to find the impact of exogenous uncertainty shocks on asset return volatilities. However, we have not specified how market uncertainty is defined or quantified yet. The CBOE volatility index is used as one of the proxies for market uncertainty. The Federal Reserve Bank of St. Louis provides the dataset. The VIX reflects market expectations of short-term volatility. The volatility is implicitly calculated using option prices of the S&P 500. The fact that Capex Academy (2022) describes the volatility index as the "fear index" indicates that it might be a good proxy for uncertainty. It is decided to use the residuals of an ARIMA(2,1,1) specification for the regression, as further explained in section 4. Hence, we estimate the model

$$\Delta VIX_t = c + \phi_1 \cdot \Delta VIX_{t-1} + \phi_2 \cdot \Delta VIX_{t-2} + \theta_1 \cdot \epsilon_{t-1} + \epsilon_t$$

and save $\hat{\epsilon_t}$. The residuals are interpreted as a surprising increase in conditional volatility. $\hat{\epsilon_t}$ is also referred to as innovation or shock in the CBOE volatility index. The augmented Dickey-Fuller test indicates that the residuals are stationary. Furthermore, the residuals of the ARIMA specification of the VIX are weakly dependent. The coefficients of the ACF approach zero sufficiently quickly.

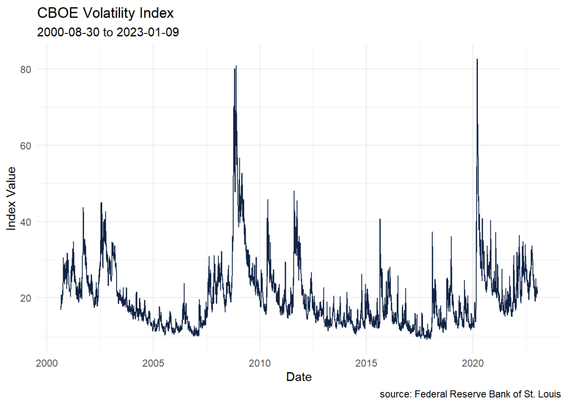


Figure 15

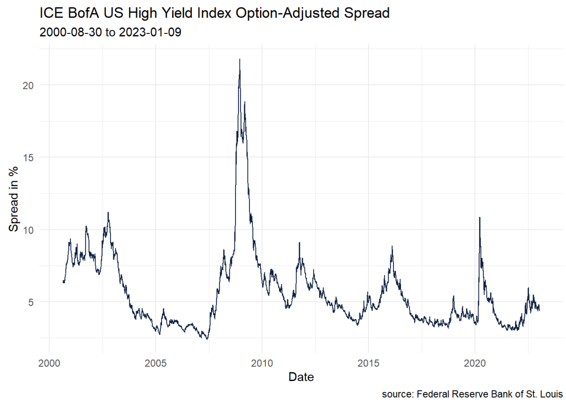


Figure 16

3.8 Credit Spreads

The Federal Reserve Bank of St. Louis provides the data for the ICE BofA Option-Adjusted Spreads (OASs). The spreads are defined as the difference between yields of corporate bonds in a certain rating category and the U.S. spot treasury yield. Hence, there exist many spread curves with different selections of indices or bonds. The data used in this paper reflect the spread for below-investment-grade rated company debt issued in the U.S. market. This time series is used as another proxy for uncertainty in financial markets. We obtain the residuals of the estimation of an ARIMA model, as they indicate surprising innovations in average credit spreads. The BIC suggests an ARIMA(1,1,1) specification this time. Hence, we obtain the residuals of the estimation of the following model.

$$\Delta CS_t = c + \phi_1 \cdot \Delta CS_{t-1} + \theta_1 \cdot \epsilon_{t-1} + \epsilon_t$$

The augmented Dickey-Fuller test indicates that the residual time series is stationary. Moreover, weak dependence is also fulfilled.

Higher and lower levels of yield spreads and the VIX occur roughly around the same periods. The average index values are at a comparably low level in 2005 and 2006. There was a sudden increase when Lehman Brothers Inc. defaulted or when the covid pandemic broke out. However, the VIX increased more in relative terms in early 2020 compared with the average credit spreads. The value of the volatility index level during the Great Recession was even exceeded. This was not the case for average credit spreads. Furthermore, the time series of the excess corporate bond yield rate fluctuates less. The unconditional variance is lower than for the VIX.

3.9 Economic Policy Uncertainty Index

We also need to control for several factors in the regressions below. We cannot include market uncertainty proxies as the sole explanatory variable. Market uncertainty depends on the general economic conditions. Hence, we are looking for an index that indicates the daily, overall well-being of an economy. We consider the Economic Policy Uncertainty Index. Scott R. Baker (Northwestern University, Kellogg School of Management), Nick Bloom (Stanford University), and Steven J. Davis (University of Chicago, Booth School of Business) developed this index to outline policy-related economic uncertainty for different countries, as we can see in Economic Policy Uncertainty (2023). The index for the United States is chosen for our purposes. The daily index value depends on three factors. One is based on newspaper research. A code is programmed that automatically searches for certain terms indicating economic uncertainty. A second component draws information from the Congressional Budget Office. Thirdly, the EPUI depends on information from the dispersion of individual forecasts of the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters.

The index sharply increased after the terrorist attacks on September 11^{th}, 2001, after the collapse of Lehman Brothers Inc., and after the outbreak of the covid pandemic. The correlation with the VIX is 0.5013. The correlation with the average yield spread on corporate loans is 0.3157.

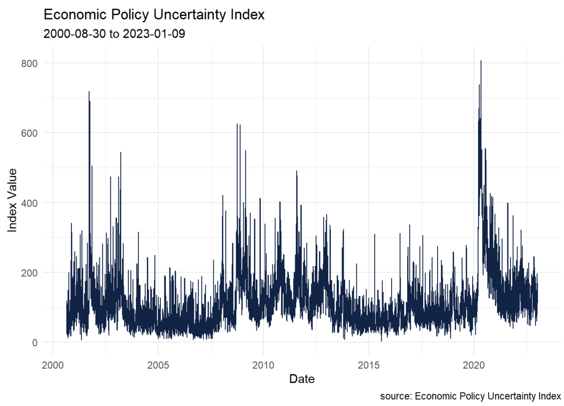


Figure 17

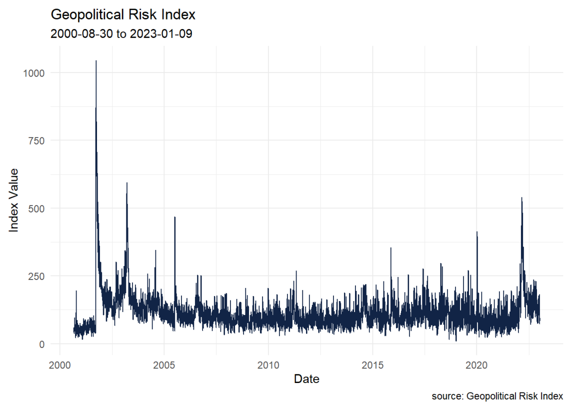


Figure 18

3.10 Geopolitical Risk Index

Similar to the Economic Policy Index, the Geopolitical Risk Index is constructed by automatically searching newspapers for predefined words indicating high geopolitical risk. The difference between the indices is that the Geopolitical Index naturally focuses on political rather than economic words and phrases. According to the authors Iacoviello and Caldara (2022), the search is based on eight categories that include War Threats, Peace Threats, Military Buildups, Nuclear Threats, Terror Threats, Beginning of War, Escalation of War, and Terror Acts. The regressions below include the GPRI as an independent variable since it is related to financial market uncertainty.

The previous three-time series are positively correlated and had similar periods of growth and decline. The GPRI does not always move in the same direction during those periods. The correlation with other financial and economic uncertainty proxies is between 0.04 and 0.1. The peak value of the GPRI is found on September 11^{th}, 2001. This index value is almost twice as high as the second-highest index value, which can be detected in 2003 when U.S. armies invaded Iraq. Other peaks occurred on the day following the terrorist attacks in London on July 7^{th}, 2005 and in Paris on November 13^{th}, 2015. High geopolitical uncertainty transpires after the Russian invasion of Ukraine. We can observe a period of lower index values during the Great Recession. The indices of financial and economic uncertainty peaked during that period.

4 Specification of Regressions

This paper aims to find the impact of an exogenous shock in market uncertainty both on the conditional volatility of assets and the growth of the conditional volatility of assets. The same regressions are run using the dynamic conditional correlation between an asset and a market portfolio afterwards. We run multiple univariate regressions to obtain the coefficient estimates regressing the differenced volatility of an asset on a proxy for market uncertainty. Since the volatility of none of the assets considered is weakly dependent, the impact of a shock in a proxy for market uncertainty on asset return volatility is measured with a multivariate VAR model, which is transformed to a $VMA(\infty)$ model to obtain the impulse response function. Hence, a univariate analysis is performed when analyzing the growth in volatility. The impacts on asset volatility are measured with multivariate analysis. The following subsections explain step-by-step how and why we ended up with our final model specifications.

4.1 Univariate Analysis

We need to specify the correct regression in order to find consistent estimates of an exogenous increase in uncertainty on asset return volatility. The goal is that the coefficient estimates are consistent such that

$$\underset{n\to\infty}{plim}\hat{\beta} = \beta$$

The first intuition is to run this simple regression.

$$\sigma_{asset,t} = \alpha + \beta \cdot MU_t + \epsilon_t$$

$\sigma_{asset,t}$ is the conditional volatility of an asset. MU_t stands for the market uncertainty proxy. High market uncertainty today is likely followed by high market uncertainty tomorrow, as we have already discussed. Hence, the residuals of an ARIMA(2,1,1) process of the logarithmic market uncertainty proxy are used. We want to know the impact of a surprising shock or innovation in market uncertainty, which is denoted by $\widetilde{MU_t}$. Using obtained residuals from other regressions as independent variable is also done by Sims (1972), which motivates the approach selected here. Note that there are also other ways to obtain the dynamic causal effect of market uncertainty shocks on asset volatility without using the residuals of a separate ARIMA regression. This could be achieved by adjusting and augmenting the final regression specification.

Hence, we rewrite the equation.

$$\sigma_{asset,t} = \alpha + \beta \cdot \widetilde{MU_t} + \epsilon_t$$

Both time series used are stationary. However, we do not get consistent estimates from this regression. We have to think about whether the conditional error mean is zero such that $E(\epsilon_t|\widetilde{MU_t}) = 0$. β is inconsistent when a potentially omitted variable is causing endogeneity, which depends on its correlation with the errors and with other regressors. Let us consider the general condition of the world economy. It impacts the volatility of assets and its correlation with the fear in financial markets is not zero. Hence, the OLS estimators are inconsistent.

The overall economic well-being cannot be measured directly. However, there exist many different macroeconomic indicators about the current state of the economy like real GDP, unemployment rate, inflation, or personal income. However, problems arise when we use those indicators as we have market uncertainty proxies and conditional asset volatilities on a daily basis. Most macroeconomic indicators are published monthly or even quarterly. Hence, there are two possibilities. We run the whole regression using the lowest frequency of all variables. The downside of this approach is that we do not know how the impacts of a shock in market uncertainty on conditional volatilities and the growth of volatilities evolve within the first months after the shock. We have to keep in mind that the main question of interest in this paper is whether the volatility and the differenced volatility of gold are impacted differently after an exogenous increase in market uncertainty compared with other assets. Let us assume the following scenario. A shock in market uncertainty does not cause the conditional volatility of gold to increase. However, it has a positive impact on the conditional volatility of the NASDAQ for the first ten days. When we use month-end data, we cannot detect a significant effect. Hence, it is decided to choose the other possibility, which is the usage of the Economic Policy Uncertainty Index, described in detail in section 4.9. The main advantage is the daily publication of the value. Furthermore, geopolitical circumstances are related to market uncertainty and are also a driver of the conditional volatility of assets. Hence, we include the Geopolitical Risk Index, for which we have daily data, as a control variable in the regression. Details about this index are provided in section 4.10. Hence, the regression looks as follows.

$$\sigma_{asset,t} = \alpha + \beta \cdot \widetilde{MU_t} + \gamma \cdot EPUI_t + \delta \cdot GPRI_t + \epsilon_t$$

One can argue that these controls do not fulfill the contemporaneous exogeneity assumption convincingly, as we do not explicitly control for specific economic data or specific politic events. We rather control for a catch-all term that states how the economy is performing and how high the geopolitical risk is. This might be problematic when we consider the following example. Real GDP growth is high, but inflation is too, which is not an unrealistic assumption. It can be argued that the controls are too rough to account for the exact circumstances, as the Economic Policy Index has only one daily value assigned. To justify the inclusion of these controls, we want to argue both from an economic and a statistical point of view. The latter is done at the end of this section when we have established the regression that we want to use. Our understanding of financial markets tells us that political risk impacts asset volatility. For example, the outbreak of a war or terrorist attacks cause changes in asset volatility as the market sentiment adapts. It can be argued that political uncertainty impacts market uncertainty, which then impacts asset volatility. This view is strengthened by the fact that the implications of geopolitical risk on the volatility of almost every asset are insignificant when we control for Economic Policy Uncertainty and market uncertainty. Economic recessions, high inflation, or an increase in the unemployment rate impact the EPUI. This causes changes in the volatility of assets as the market sentiment adapts too. Hence, both the GPRI and EPUI are included because our intuitive understanding of financial markets tells us that they belong in the regression. This intuition is strengthened by papers like Ho et al. (2013) and Beaulieu et al. (2005), which find that those factors drive asset volatility.

We run the regression on h different leads of the explained variable, as we want to know how the impacts of a shock in the market uncertainty proxy on the volatility of an asset evolve over time. As a result, the model specifications look as follows

$$\sigma_{asset,t+h} = \alpha + \beta \cdot \widetilde{MU_t} + \gamma \cdot EPUI_t + \delta \cdot GPRI_t + \epsilon_{t+h}$$

for h in range $[0 : \Psi]$, where Ψ is chosen depending on how many periods we are interested in.

There are five asymptotic properties of OLS for regressions with time series data, according to Wooldridge (2002).

TS.1' Assumption of linearity in parameters, stationarity, and weak dependence

TS.2' No perfect collinearity

TS.3' Contemporaneous exogeneity $E(u_t|x_t) = 0$

TS.4' Homoscedasticity such that $Var(u_t|x_t) = \sigma^2$

TS.5' No serial correlation such that $E(u_t, u_s) = 0$ for all $t \neq s$

TS.1'-TS.3' are necessary for OLS consistency. OLS estimators are asymptotically normally distributed and standard errors are asymptotically valid when TS.1' - TS.5' are fulfilled.

We have to ask whether the regression above fulfills these requirements. Two problems arise. First of all, the volatility of assets is not weakly dependent, as volatilities are very persistent. Hence, TS.1' is not fulfilled. As a result, we take the first difference of asset volatilities. It is shown that the decay of the ACF of differenced volatilities is sufficiently quick. Furthermore, all variables are stationary, as we can see in the appendix.

Another problem arises as the residuals of an ARIMA specification of the Volatility Index are correlated with lags of the Economic Policy Uncertainty Index and the Geopolitical Risk Index. Hence, we control for lags of the EPUI and GPRI. The lag order is decided based on a function that finds the optimal number of lags, according to the suggestion of the $\bar{R}^2$. Note that the adjusted R squared is an adaption of the R squared, which indicates the share of the variation explained in the dependent variables by the independent variables. $\bar{R}^2$ penalizes overfitting. Our final specification looks as follows when we take these two adjustments into account.

$$\Delta\sigma_{asset,t+h} = \alpha_h + \beta_h \cdot \widetilde{MU_t} + \gamma_{1,h} \cdot \Delta EPUI_t + ... + \gamma_{m,h} \cdot \Delta EPUI_{t-m} +$$

$$\delta_{1,h} \cdot \Delta GPRI_t + ... + \delta_{n,h} \cdot \Delta GRPI_{t-n} + \epsilon_{t+h}$$

, where $\Delta\sigma_{asset,t+h}$ is the differenced volatility of an asset. $\widetilde{MU_t}$ indicates the residuals of an ARMA specification of the selected logarithmic market uncertainty proxy. $\Delta EPUI$ and $\Delta GPRI$ indicate the differenced logarithmic Economic Policy Uncertainty Index and the differenced logarithmic Geopolitical Risk index. M and n are decided based on the adjusted R^2. As we are running a level-log regression, the interpretation is that a 1 % shock in the explanatory variable causes the explained variable to increase by $\frac{\beta_h}{100}$, $\frac{\gamma_h}{100}$ or $\frac{\delta_h}{100}$ % in expectation.

This regression specification fulfills TS.1'. We perform ADF tests for all variables. The null hypothesis of a unit root is rejected for all variables. Furthermore, all dependent and independent variables fulfill weak dependence. Our model is linear in parameters and there is no perfect multicollinearity. The assumption is that TS.3' is also fulfilled. Obviously, ϵ_{t+h} for h>0 is independent of contemporaneous dependent variables, as there are none in the regression. The regressions solely contain lagged variables except for h=0. Contemporaneous exogeneity is fulfilled when h is equal to zero too as we control for economic policy uncertainty and geopolitical risk. Both are assumed to be correlated with the volatility index and have explanatory power for asset volatility. Hence, OLS estimators are consistent.

TS.4 and TS.5 are checked before we run the regressions with distributed lags. Both are usually not fulfilled in time series regressions. This is problematic as the usual inference statistics are incorrect. Hence, we use Newey West standard errors that control for heteroskedasticity and autocorrelation in error terms, which were proposed by Newey and West (1987). Using HAC standard errors in a dynamic model can be problematic. The cause for the autocorrelation in the errors might be the misspecification of a model. However, we have regressions with distributed lags, as there are no lags of asset volatility as explanatory variables. The problem of serial correlation or heteroskedasticity does not arise for some regressions. The usual standard errors or heteroskedasticity-adjusted standard errors are used in these cases.

Even though there is no perfect multicollinearity, strong multicollinearity can also cause problems. Hence, the Variance Inflation Factor is constructed which is smaller than two for all regressions considered in this paper. There is a rule of thumb that states that multicollinearity is not a problem as long as all VIFs are smaller than 10, according to James et al. (2017).

The coefficients of the Economic Policy Index are statistically significant for most assets, even when we control for a market uncertainty proxy and geopolitical risk. Moreover, $\bar{R}^2$ increases. Hence, the inclusion of the EPUI is justified from an economic and statistical point of view. $\bar{R}^2$ increases when the GPRI is included. Its exclusion leads to inconsistent estimates. As a result, the GPRI is also included in all regressions, even though its coefficients are rarely statistically significant when we control for a market uncertainty proxy and geopolitical risk.

4.2 Multivariate Analysis

We have specified a model to analyze the relationship between the growth of the conditional volatility of assets and market uncertainty in the previous subsection. Now, we use a multivariate model to investigate how conditional volatility and market uncertainty are related. The approach to finding the correct model specification and the transformation of the VAR(k) to obtain the impulse response function is suggested by Tsay (2005). Therefore, we specify a VAR(k) model where the lag number p is decided based on the Akaike Information criterion.

$$\begin{pmatrix} log(\sigma_{asset,t}) \\ log(MU_t) \\ log(EPUI_t) \\ log(GPRI_t) \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \\ \phi_{30} \\ \phi_{40} \end{pmatrix} + \begin{pmatrix} \phi_{1,11} & \phi_{1,12} & \phi_{1,13} & \phi_{1,14} \\ \phi_{1,21} & \phi_{1,22} & \phi_{1,23} & \phi_{1,24} \\ \phi_{1,31} & \phi_{1,32} & \phi_{1,33} & \phi_{1,34} \\ \phi_{1,41} & \phi_{1,42} & \phi_{1,43} & \phi_{1,44} \end{pmatrix} \begin{pmatrix} log(\sigma_{asset,t-1}) \\ log(MU_{t-1}) \\ log(EPUI_{t-1}) \\ log(GPRI_{t-1}) \end{pmatrix}$$

$$+ ... + \begin{pmatrix} \phi_{k,11} & \phi_{k,12} & \phi_{k,13} & \phi_{k,14} \\ \phi_{k,21} & \phi_{k,22} & \phi_{k,23} & \phi_{k,24} \\ \phi_{k,31} & \phi_{k,32} & \phi_{k,33} & \phi_{k,34} \\ \phi_{k,41} & \phi_{k,42} & \phi_{k,43} & \phi_{k,44} \end{pmatrix} \begin{pmatrix} log(\sigma_{gold,t-k}) \\ log(MU_{t-k}) \\ log(EPUI_{t-k}) \\ log(GPRI_{t-k}) \end{pmatrix} + \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \end{pmatrix}$$

Insignificant parameters at the 5 % significance level are removed. Cross-correlation matrices are investigated to check the adequacy of a model specification. No significant serial and cross-sectional correlations should remain in the residuals. We run the multivariate Portmanteau test with the null hypothesis

$$H_0 : \boldsymbol{R_1} = ...\boldsymbol{R_m} = \boldsymbol{0}$$

, where $\boldsymbol{R_i}$ indicates the theoretical lag i cross-correlation matrix of innovations.

By repeated substitution, the VAR(k) model is transformed into an $VMA(\infty)$ model. From a $VMA(\infty)$ model, we can directly obtain the impulse response function. We are especially interested in the [1,2]-element of the coefficient matrices of the transformed model. All variables used in the multivariate time series regression are stationary. The ADF test indicates that the time series is not stationary when credit spreads are used as a market uncertainty proxy. Hence, $log(MU_t)$ is replaced with ΔMU_t in order to make the time series stationary. The interpretation of the impulse response function with the logarithmic proxy is that a 1 % shock in the market uncertainty proxy causes the volatility of an asset to increase by the functional value in %. The interpretation is that a unit increase in the differenced market uncertainty proxy causes the volatility of an asset to increase by the functional value of the impulse response function times 100 when ΔMU_t is used. A Cholesky transformation of the variance-covariance matrix is performed to achieve orthogonalization. The confidence bands are calculated with the bootstrapping method. The number of repetitions is between 75 and 300. If the null hypothesis rejects sometimes and sometimes fails to reject, a higher number is selected.

5 Impacts of uncertainty shocks on GARCH based volatility

5.1 Volatility Index

5.1.1 Gold

In this subsection, we plug differenced conditional gold volatility as explained variable and the VIX as a market uncertainty proxy in the final regression specification of subsection 5.1.

The Ljung-Box test indicates that there is no serial correlation in the error terms. However, the null hypothesis of homoscedasticity is rejected, as the Breusch-Pagan test and the White test point out. Hence, we use White standard errors for the regressions.

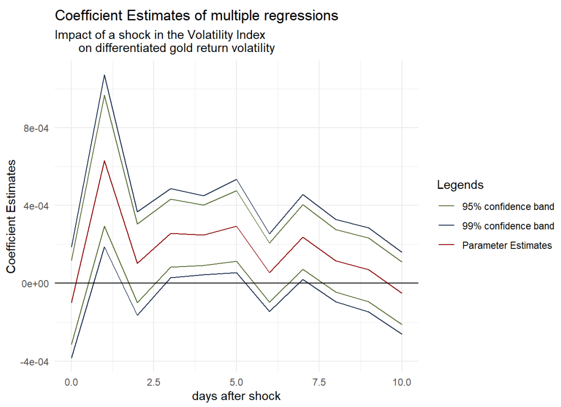


Figure 19

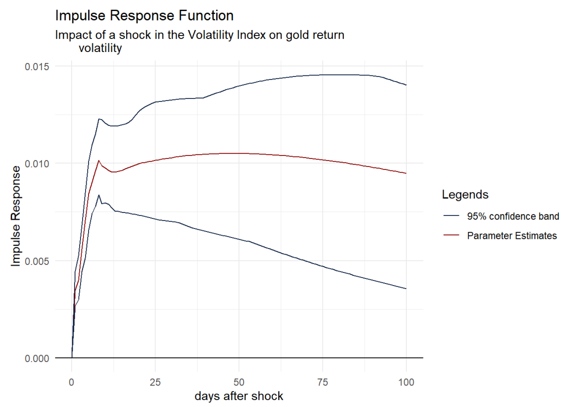


Figure 20

The red line in figure 19 indicates $\hat{\beta_h}$ over time, while the green line shows the 95 % confidence bands and the blue line the 99 % confidence bands. The necessity to run the regression on leads of differenced gold volatility can be observed immediately. If we solely regressed on contemporaneous volatility, the result would be that there is no significant impact. However, there is a dynamic causal effect. The biggest impact of an exogenous increase in the volatility index occurs after one day. Then the coefficient estimate decreases and no significant effects can be found for h equal to two. However, we can reject the null hypothesis that β_h is zero for three to seven days after the initial shock, with the exception of the sixth day. The interpretation of the coefficient estimates is that a 1 % shock or innovation in the VIX is expected to increase the differenced gold return volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. It might be surprising that the coefficient estimates are significant but small. The economic relevance of market uncertainty shocks on gold price volatility might be questioned.

However, we have to keep in mind that the unexpected increase in the volatility index is used as an explanatory variable, which was obtained keeping the residuals of an ARIMA specification. This explains why the R^2 of the regression is comparably low, as solely the surprising part of the VIX is included in the regression. Furthermore, we measure the effect unrelated to present and past geopolitical and economic uncertainty. One might be tempted to state that the impact on gold volatility is the biggest after one day following a shock in the VIX. This is incorrect, as the dependent variable is differenced gold volatility. As there are significant impacts for up to seven days after the initial shock, gold volatility is still expected to increase. As gold volatility is highly serially correlated, shocks in the VIX impact gold volatility for a long time. This can be seen in figure 20. The impact of a shock in the volatility index on gold return volatility is calculated by transforming a VAR(10) into an $VMA(\infty)$ specification. Section 5.2. provides further details about the econometric approach. The interpretation of the coefficients is that a 1 % increase in the VIX causes gold volatility to increase by the value indicated by the impulse response function in %. We can see that the results of the univariate regressions and the multivariate regression are similar when we keep in mind that the explained variable is volatility growth in figure 19 and volatility in figure 20. The volatility of gold increases quickly and the coefficient estimates have a local maximum seven days after a market uncertainty shock. We can see that the decline is slow. The coefficient estimates 100 days after the initial shock are just below the estimated value seven days after the shock. This result is not a surprise when we look at the autocorrelation function of gold, which indicates that the correlation coefficients are significantly different from zero for more than 100 lags. The 95 % confidence bands never include the value zero. Hence, the effects are statistically different from zero at the 5 % significance level. The R^2 of the multivariate regression is higher than the R^2 of the univariate regression. This result is not a surprise, as lagged logarithmic VIX observations are included as explanatory variables in the multivariate regression. The CBOE Volatility Index, the Economic Policy Uncertainty Index, and the Geopolitical Risk Index can explain most of the variation in gold volatility in the multivariate model. The sharpest increase is within the first seven days, which is in accordance with the results from figure 19. When we take a closer look at figure 20, the growth of the coefficient two days after the shock is smaller than for most of the other first seven days, which explains why the coefficient for h equal to 2 in figure 19 is insignificant. Similar patterns of the coefficient estimates are detected frequently. Economically, it seems as if the volatility increases disproportionally or even overshoots one day after the shock. Hence, the increase is insignificant or is sometimes even negative and significant on the second day, as we will later see.

The coefficient of the EPUI, which is denoted as $\gamma_{1,h}$, is interpreted as the impact of a 1 % increase in the differenced Economic Policy Uncertainty Index on differenced gold volatility divided by 100 when we control for the CBOE Volatility Index, the Geopolitical Risk Index and lags of the differenced Economic Policy Uncertainty Index. We can reject the null hypothesis that $\gamma_{1,h}$ is zero for h equal to 1 at the 5 % significance level. The interpretation of the coefficients of the Geopolitical Risk Index is that a 1 % increase in the differenced Geopolitical Risk Index causes differenced gold volatility to increase by the value of the parameter estimate divided by 100 when we control for the Economic Policy

Uncertainty Index, the CBOE Volatility Index and lags of the differenced Geopolitical Risk Index. We can reject the null hypothesis that $\delta_{1,h}$ is zero for h equal to 0. The graphs displaying $\gamma_{1,h}$ and $\delta_{1,h}$ are found in the appendix.

It is clear that the explanatory variables cause the explained variable since regression is run for $h \geq 0$. It is logically impossible that the explained variable causes the explanatory variables for $h > 0$. When h is equal to zero, the contemporaneous effects are measured. However, an increase in the differenced volatility of gold does not cause the residuals of the proxy for market uncertainty to increase. A Granger test shows that the residuals of an ARIMA specification of the VIX Granger cause differenced gold volatility, but not the other way around. $\Phi_{i,12} \neq 0$ for some i, but $\Phi_{i,21} = 0$ for all i in the multivariate model. Hence, we have a unidirectional relationship between gold volatility and the VIX.

Beckmann et al. (2019) claim that the reaction of gold returns in times of uncertainty changed since the end of the Great Recession. Hence, a test proposed by Chow (1960) is performed. The null hypothesis is that there is no structural change. The idea is to break up the time series at a predefined date. The sum of squared residuals of the two regressions is at the highest the sum of squared residuals of the regression using the whole timeline. Usually, it is lower. Then it is tested whether the improvement in fit is statistically significant. It is decided to use July 1^{st}, 2009 as a break date. This day marked the official ending of the Great Recession, according to National Bureau of Economic Research (2023). For gold, we can reject the null hypothesis of the Chow test. Hence, we can confirm the results by Beckmann et al. (2019). Additionally, the null hypothesis is rejected when February 24^{th}, 2022 is the structural break day. This date marked the official beginning or intensification of the Russo-Ukrainian war. This result motivates that we cannot automatically assume that the findings in this and the following chapters mean that the volatility of gold is affected less than the volatility of other assets in the future. Further research can be conducted to see whether gold still possesses the characteristics found in this paper when solely data after the beginning of the Covid crisis or the beginning of the Russo-Ukranian war are selected.

The results of both the univariate regressions with distributed lags and the impulse response function of the transformed VAR indicate that gold volatility is expected to increase following a shock in the VIX when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. Moreover, economic and geopolitical risks positively impact gold return volatility. As a result, gold volatility is not completely unaffected by exogenous changes in market uncertainty, and geopolitical or economic risk. However, we compare these results to those of other assets to put the reaction of gold volatility in perspective.

5.1.2 SP500

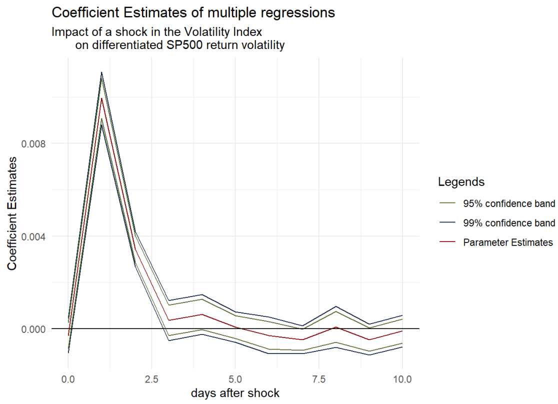


Figure 21

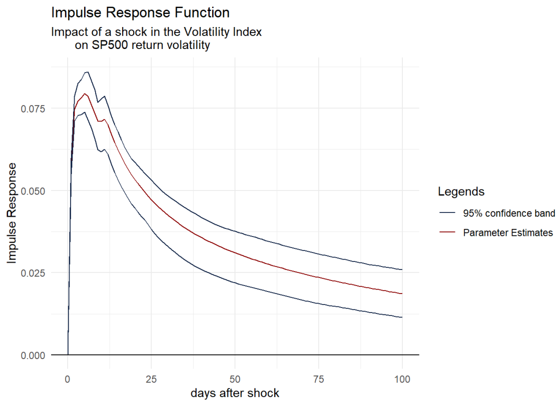


Figure 22

A 1 % shock or innovation in the VIX is expected to increase differenced conditional SP500 return volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h equal to 1 and 2. The impacts on differenced SP500 volatility are 15.8 times those on gold volatility one day after the market uncertainty innovation. Furthermore, the effects on the growth of SP500 volatility are solely significant for two days. We cannot reject the null hypothesis that the coefficients are zero at the 1 % significance level for h bigger than 3. Significant impacts are found for gold for up to six days after the initial shock. Furthermore, there is no local minimum in the coefficient estimates two days after the initial shock, as we have seen for gold. Generally, the question arises why there is no immediate significant effect. This is surprising as the efficient market hypothesis states that information is incorporated immediately. The answer is that conditional GARCH-based volatility depends solely on past values. As the data are provided at a daily frequency, today's volatility solely depends on observations from previous days. Hence, we can neither confirm nor deny whether a shock in market uncertainty leads to higher volatility on the same day. We calculate the volatilities of assets using an approach by Garman and Klass that use intraday prices in their formula in later sections. Figure 22 indicates the impact of a shock in the volatility index on SP500 return volatility. A VAR(10) specification is chosen by the AIC this time. The coefficient estimates reach a level up to almost 0.08, which is approximately eight times the peak of the coefficient estimates of gold. Furthermore, the graph increases even more quickly than for gold, which is in line with what we have seen in the regression with differenced volatility as the dependent variable. Since the serial correlation of the SP500 is lower than for gold, the coefficient estimates decline more quickly. There are still significant impacts on the SP500 return volatility 100 days after the shock, even though the coefficient estimates are approximately a quarter of the maximum impact.

A 1 % increase in the differenced Geopolitical Risk Index is expected to increment differenced SP500 volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index, the CBOE Volatility Index, and lags of the differenced Geopolitical Risk Index. We can reject the null hypothesis that $\delta_{1,h}$ is zero for h equal to zero and five at the 5 % significance level. The interpretation is similar for $\gamma_{1,h}$. We cannot reject the null hypothesis that the coefficients are zero for h equal to zero at the 1 % level. The coefficient estimates decrease for higher h. The null hypothesis that the coefficients are zero cannot be rejected anymore.

The null hypothesis of the Chow test is rejected when July 1^{st}, 2009, and February 24^{th}, 2022 are selected as break-date.

We have already pointed out that the coefficient estimates for the SP500 are bigger than those from gold. Naturally, we also want to make statistical inferences and test the hypothesis of whether the coefficients are different from each other. A test proposed by Clogg et al. (1995) allows us to compare coefficients from different non-nested regressions. The null hypothesis is that the two coefficients are the same such that $H_0 : \beta_r = \beta_s$. The test statistic follows a standard normal distribution under the null hypothesis and is calculated by the following formula

$$Z_h = \frac{\hat{\beta}_{hSP500} - \hat{\beta}_{hgold}}{\sqrt{se(\hat{\beta}_{hSP500})^2 + se(\hat{\beta}_{hgold})^2}}$$

We plot the p values over time and draw a horizontal line at $y = 0.05$. Hence, it is directly observable for which h the p values are below 0.05. We can reject the null hypothesis that the coefficients are the same for days when the p-value is below the horizontal line.

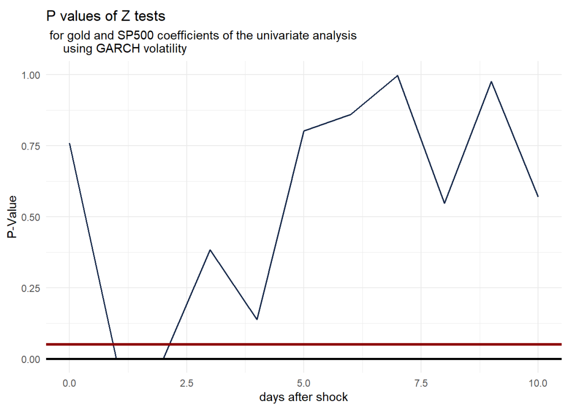


Figure 23

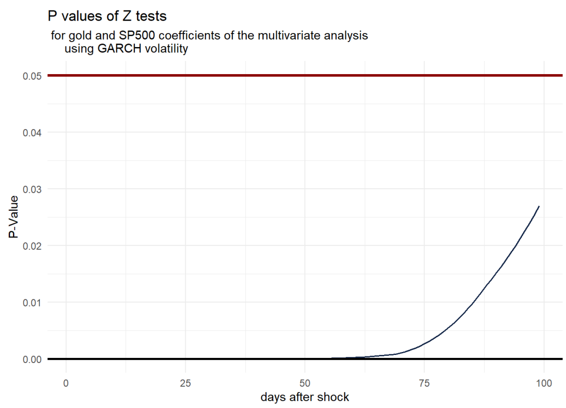


Figure 24

Figure 23 shows that the coefficients of the univariate regressions are significantly different from each other for h equal to one and two. The growth of gold volatility is less impacted by a shock in the VIX than the increase in volatility of the SP500 as the coefficient estimates of gold are also smaller than those of the SP500. We can reject the null hypothesis that β_h for the regression with differenced gold volatility as explained variables are zero for some h bigger than three, as we see in figure 19. However, the coefficients of gold are indistinguishable from the coefficients of the regression with differenced SP500 volatility as the dependent variable. The p values of the Z tests of the coefficients of the impulse response functions of gold and the SP500 are below 0.05 for the first 97 days after the innovation. Once again, as the coefficient estimates of gold are lower, we conclude that the impacts of a shock in the VIX on conditional gold volatility are smaller than the effects on conditional SP500 volatility.

The results of both the univariate and multivariate regressions indicate that SP500 volatility is expected to increase following a shock in the VIX as the coefficients are significantly different from zero when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. The effects on the growth of SP500 return volatility are significantly different from those on gold. For the multivariate analysis, gold coefficients are significantly different from SP500 coefficients for more than 100 days after the shock. Economically, these results are not unexpected. The VIX is directly calculated using SP500 index option prices, according to Federal Reserve Bank of St. Louis (2023). Hence, it is intuitive that the expected volatility derived from SP500 option prices impacts the conditional volatility of the index more than the conditional volatility of gold. This emphasizes the need for robustness checks, using another proxy for market uncertainty.

5.1.3 NASDAQ

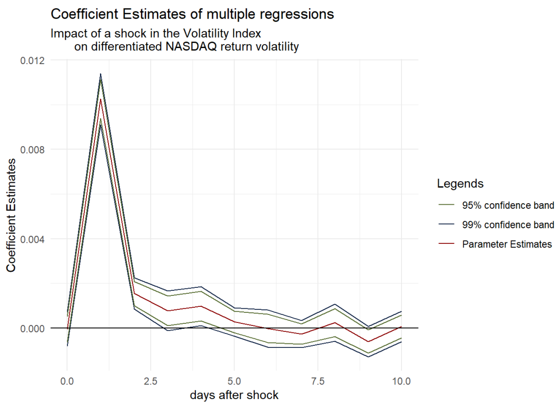


Figure 25

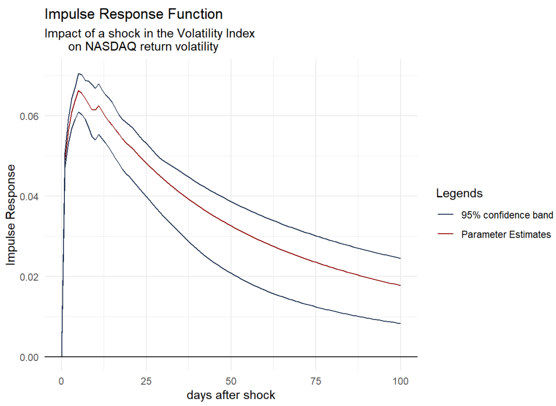


Figure 26

A 1 % shock or innovation in the VIX is expected to increase differenced NASDAQ return volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h equal to 1, 2, and 4 at the 1 % significance level. For h equal to three, we can reject the null hypothesis that the coefficient β_3 is zero at the 5 % significance level. The biggest impact of a shock in the market uncertainty proxy on differenced NASDAQ is found after one day, as the coefficient estimate is 0.01026, which is 16.29 times the coefficient estimate of the regression with gold. The coefficients are not significantly different from zero at the 1 % level after four days. Figure 26 displays the impulse response of a shock in market uncertainty on NASDAQ volatility. The peak of the graph is reached after five days. The effects of a shock are still significant after 100 days because of the persistence of NASDAQ volatility. However, these coefficient estimates are approximately a third of the biggest ones found within the first few days after the shock. The results of the regression with gold as explained variable are different. The peak impact of the regression with differenced NASDAQ volatility as the explained variable was higher than the regression with differenced SP500 volatility. However, the biggest coefficient estimate for the impulse response function is found for the SP500 and not the NASDAQ. Figure 25 shows that the impact on the growth of SP500 volatility is almost twice as much as the impact on NASDAQ volatility two days after the initial shock. This explains the findings from figure 26

Moreover, the $\gamma_{1,h}$ is significant for h equal to zero at the 1 % significance level and $\delta_{1,h}$is significant for h equal to zero at the 5 % significance level. Hence, a shock in economic policy uncertainty impacts the growth in NASDAQ volatility even when we control for lags of economic policy uncertainty, geopolitical uncertainty, and market uncertainty. Similarly, a shock in geopolitical uncertainty causes NASDAQ volatility to increase even when we control for lags of the GPRI, economic policy uncertainty, and market uncertainty. The graphs with the coefficient estimates and the confidence bands are displayed in the appendix. The null hypothesis of the Chow test is rejected for both dates considered, indicating the presence of a structural break.

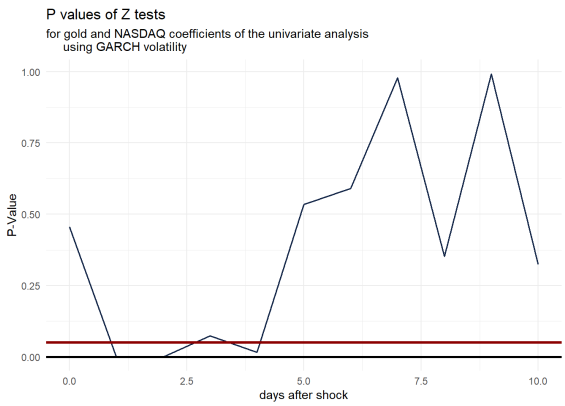


Figure 27

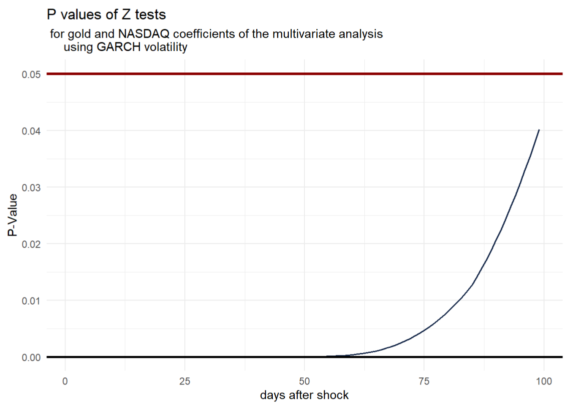


Figure 28

Graph 27 indicates that the p-values of multiple Z tests for gold and NASDAQ coefficients are below 0.05 for h=1,2 and 4. The coefficients of the univariate regression with differenced NASDAQ volatility as an explained variable were significantly different from zero at the 1 % level for these lags. We conclude that shocks in the CBOE volatility index impact gold volatility less than NASDAQ volatility, as the coefficient estimates for gold are smaller than those for NASDAQ. The null hypothesis that the coefficients of the impulse response function are the same is rejected for the first 100 days after the innovation.

The results of both the univariate and multivariate regression indicate that conditional NASDAQ volatility is expected to increase following a shock in the VIX as the coefficients are significantly different from zero controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. The effects on NASDAQ return volatility are also significantly different from those on gold. Gold volatility is less sensitive to changes in the market than NASDAQ volatility. The reason might be that gold is mainly an investment asset and its industrial usage is relatively low, as it is solely used as jewelry and in some technological branches according to O'Connor et al. (2015). The economic impact of high market uncertainty on private demand for luxury goods is negative, according to Jiachen (2022). However, central banks and private investors tend to increase demand in times of high market uncertainty, which may stabilize price fluctuations. On the other hand, high uncertainty about the demand and supply of products of tech companies in times of financial turmoil leads to higher fluctuations in the NASDAQ index.

5.1.4 Oil

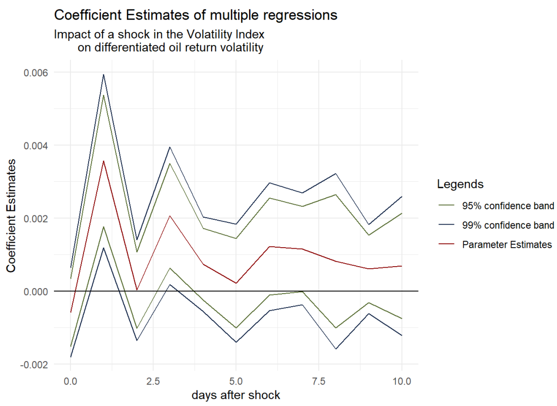


Figure 29

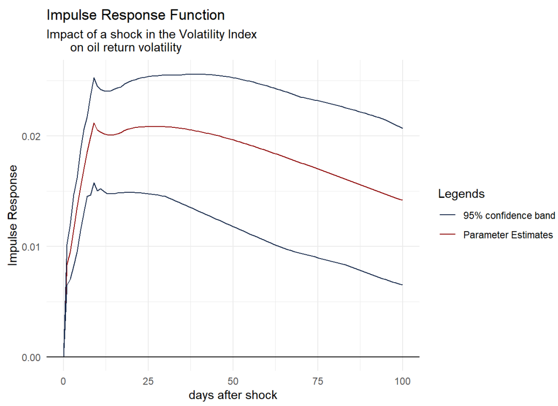


Figure 30

A 1 % shock or innovation in the VIX is expected to increase differenced oil return volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h=1 and h=3 at the 1 % significance level. The biggest coefficient estimate of a market uncertainty shock is 0.003569, which is lower than the biggest one from the SP500 or NASDAQ. However, the peak coefficient estimate is still 5.66 times the one from the gold regression. No significant impacts on the growth of copper volatility are found after three days. Once again, the impacts on growth are the highest one day after the shock, decrease on the second day, and then increase again. We have seen this phenomenon before. Figure 30 shows that the volatility growth is only slightly positive on the second day after the shock. It takes nine days until the biggest impact of a shock in market uncertainty on oil volatility is reached. This is longer than for the SP500 and the NASDAQ. However, the biggest coefficient estimate is slightly above 0.02, which is smaller than the one from the regression with NASDAQ and SP500 volatility as the dependent variable. The effects are still significant after 100 days and approximately 75 % of their highest level. This shows the persistence of oil volatility.

Note that exogenous shocks neither in the Economic Policy Uncertainty Index nor in the Geopolitical Risk Index impact the growth of oil volatility significantly. The null hypothesis of the Chow test is rejected for both dates considered.

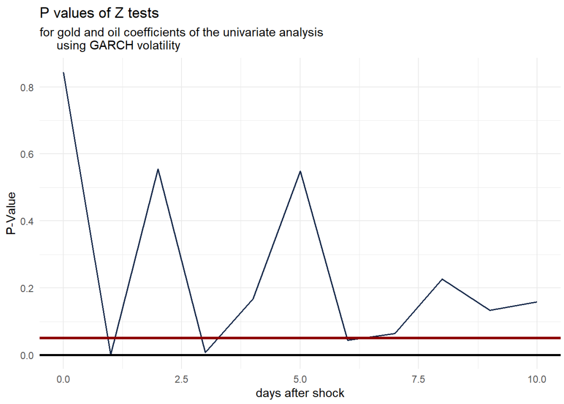


Figure 31

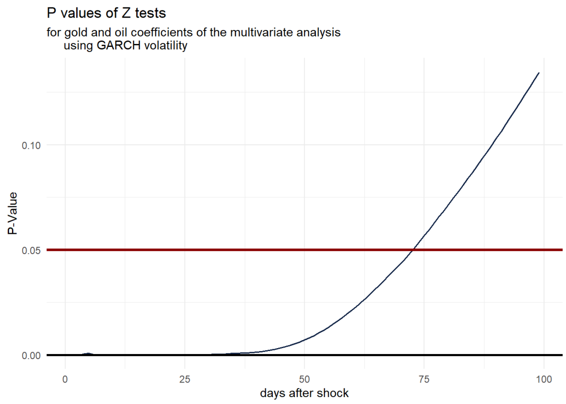


Figure 32

Graph 31 indicates that the p-values of the Z-tests are below 0.05 for h=1,3, and 6. As the coefficient estimates of gold are smaller than those of oil, shocks in the CBOE volatility index impact gold volatility less than oil volatility. Gold was solely compared to market indices consisting of shares of different firms so far. Hence, the properties of gold are compared to those of other natural resources. Our findings are that gold has unique characteristics in times of uncertainty. The coefficients of gold and oil are significantly different for the first 73 days after the shock when we consider the p-values of the Z tests of the coefficients of the impulse response function.

The univariate and multivariate analysis indicates that oil volatility is expected to increase following a shock in the VIX as the coefficients are significantly different from zero when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. Compared with gold, the effects on oil return volatility are significantly dissimilar. Even though both gold and oil are natural resources, their economic usage explains why the reactions differ that much. As we have already pointed out, gold is intrinsically valued as stable by people, while it has low industrial usage. On the other hand, oil does not have this reputation. It is mainly used as a fuel, and energy provider but also in the chemical industry, according to Tiger General (2016). Hence, its price is dependent on the demand of firms, which fluctuates when there is high market uncertainty. Furthermore, it might not be economically intuitive, why oil volatility does not depend on shocks in the EPUI or GPRI, while conditional gold, NASDAQ, and SP500 volatility do. However, we have to consider that $\gamma_{1,h}$ and $\delta_{1,h}$ indicate the impact on the growth of volatilities of assets when we control for the volatility index as a proxy for market uncertainty. Hence, this does not mean that the growth in oil volatility does not react at all to geopolitical and economic uncertainty. It means that there is no reaction in differenced oil volatility when controlling for market uncertainty.

5.1.5 Copper

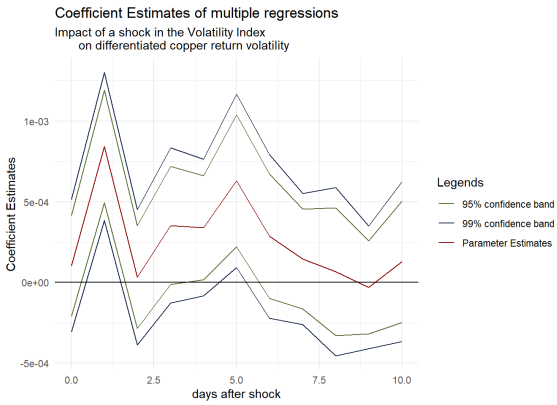


Figure 33

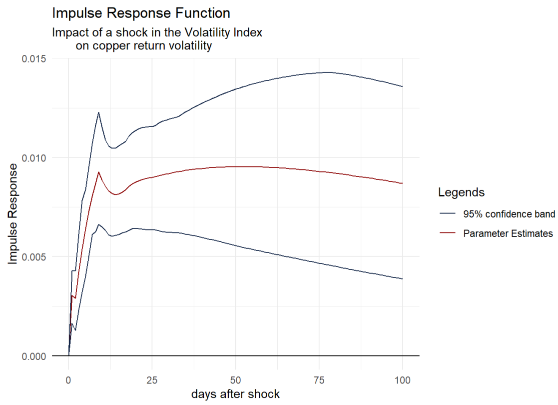


Figure 34

A 1 % shock or innovation in the VIX is expected to increase differenced copper volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h equal to one and five at the 1 % significance level. The coefficient β_4 is different from zero at the 5 % significance level. As we have seen for gold and oil, the graph has a local minimum for h equal to two. Intuitively, we expect the coefficients to decline gradually after the peak was reached. However, this is not the case. No impacts on differenced copper volatility are found at the 5 % significance level two and three days after the initial innovation. The values are of the same order of magnitude as those for gold. The biggest coefficient estimate for the regression with differenced copper volatility as the dependent variable is 0.000842. This value is 33.7 % higher than the value of the peak coefficient estimate of the regression with gold. It was already anticipated that the null hypothesis of the Z tests is rejected for certain h for the other assets considered so far. The upper 99 % confidence band of the regression with differenced gold volatility was far away from the lower 99 % confidence bands of the regression with another asset. However, the results of the Z tests are not clear this time prior to its calculation. Figure 34 indicates the impact of a shock in the VIX on copper return volatility. A VAR(10) model is chosen by the AIC. Once again, the growth of the function is low two and three days after the innovation. This is in accordance with the results of the univariate regression with differenced copper volatility as the response variable. A local maximum is found ten days after the shock. Compared with the impulse functions for the NASDAQ and the SP500, it takes comparably long until a local maximum is reached. This is not a surprise as the coefficient estimates in figure 33 are positive for a rather long time, even when they are not significantly different from zero. The coefficient estimates in figure 34 decrease 10 to 14 days after the innovation. However, this is not the beginning of a gradual decline in the coefficient estimates, as an increase in the impulse response function follows. The coefficient estimates 55 days after the innovation are significant and bigger than the coefficient estimates for h equal to 10. There is a very gradual decline afterwards. The shape of the impulse response function is similar to the one of gold, as high persistency is observed. It is not economically intuitive why the impact of a shock on copper volatility is lower 12 days after the shock than 50 days after the shock when there was already a peak impact after ten days. Figure 20 depicts that the graph for gold reaches higher values than in figure 34. Gold has a special characteristic in terms of the reaction of its volatility in times of crisis compared with the other assets considered so far. However, the volatility of this metal reacted similarly to the volatility of gold.

Moreover, $\gamma_{1,h}$ is significant for h equal to zero at the 5 % significance level, and $\delta_{1,h}$ is significant for h equal to three at the 5 % significance level. Exogenous shocks in geopolitical risk or economic policy risk impact the volatility growth of copper beyond market uncertainty. Next, it is tested whether we can reject the null hypothesis that the coefficients of gold and copper volatility are the same.

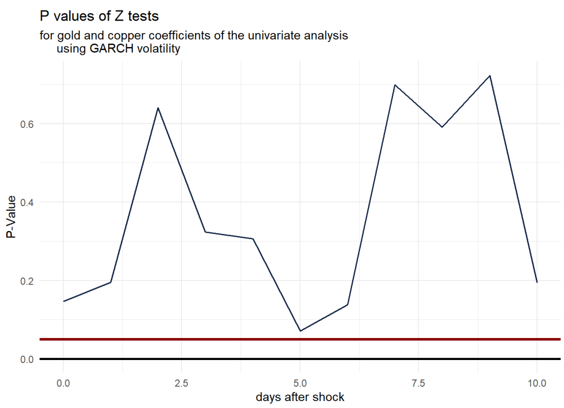


Figure 35

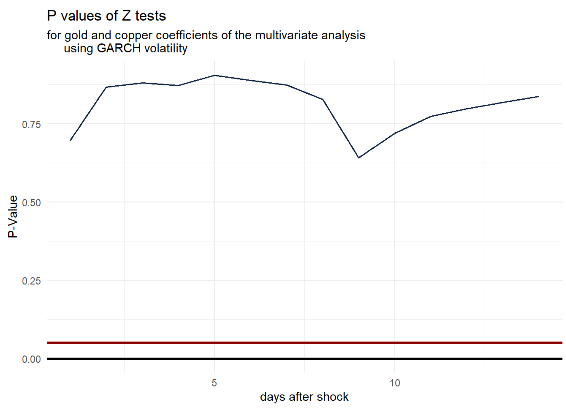


Figure 36

Figure 35 indicates that the p-values of the Z tests are never below 0.05. We conclude that shocks in the CBOE volatility index do not impact gold volatility differently than copper volatility. The same is found for the coefficients of the multivariate analysis. Even though the coefficient estimates for copper are smaller, we cannot state that the coefficients are significantly different from each other.

We fail to reject the null hypothesis of the Chow test for both dates of interest. We rejected the null hypothesis for all other assets considered so far. Copper shares several characteristics with gold. Both are metals and the growth in their conditional volatilities is indistinguishable. Despite those similarities, the role of copper in times of crisis did not change after the end of the Great Recession or the outbreak of the Russo-Ukrainian war.

The results of the univariate and multivariate analysis indicate that copper volatility is expected to increase following a shock in the VIX as the coefficients are significantly different from zero when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. However, gold and copper volatility are not impacted differently. This is noteworthy, as gold is not the only asset whose volatility is impacted that little by market uncertainty shocks. From a chemical point of view, copper is also a metal, though not a precious metal. The industrial significance of copper is higher than that of gold, as it is an essential metal for electric cables, according to Smart Assets LLC (2022). Even though there is demand for copper as an investment asset, the share of industrial usage is way higher than for gold, as stated by Provident Metals (2023). Copper was used for coin minting and Sweden even introduced a copper standard in 1624, as stated by the history of the Sveriges Riksbank (2023). This outlines that people also intrinsically value copper. Because of its large share of industrial usage, the intuition is that copper volatility should increase more than gold volatility in times of high uncertainty. However, its volatility reacts indistinguishably from gold volatility. Interpreting the results that gold volatility is similar to copper volatility in times of market uncertainty is incorrect. Unconditional copper volatility is higher than unconditional gold volatility. As the volatilities of the two metals increase indistinguishably from each other in times of market uncertainty, gold volatility is lower on average in times of high market turmoil.

5.1.6 Silver

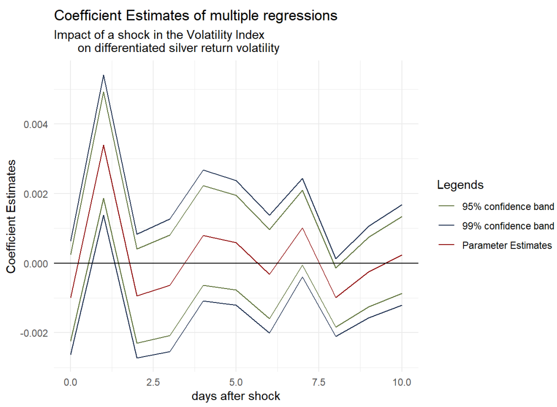


Figure 37

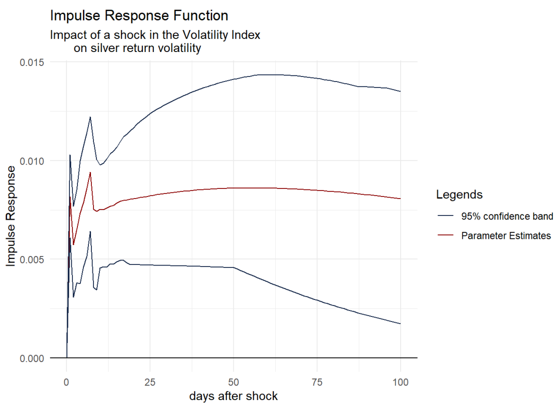


Figure 38

A 1 % shock or innovation in the VIX is expected to increase differenced silver return volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h=1 at the 1 % significance level. As silver is a metal like copper and a precious metal like gold, we expect that the impact of a shock in the market uncertainty proxy is roughly the same. However, this is not the case as positive significant effects on differenced silver volatility are found for the first day only. The coefficient estimates are negative for h equal to two, three, six, and eight. We can even reject the null hypothesis that coefficient β_8 is zero eight days after the shock at the 5 % significance level. Furthermore, the biggest coefficient estimate of the regression with differenced silver volatility as the dependent variable is 5.38 times the biggest coefficient estimate. The confidence bands in figure 37 cause us to expect that the null hypothesis of the Z-test can be rejected. The shape of the impulse response function is not a surprise, as the coefficient estimates of the univariate regression fluctuate around zero for h bigger than one. Figure 38 shows the immediate increase in volatility after the innovation in the market uncertainty proxy, which is followed by a decrease and an even further increase in the function. We can also see the statistically significant decrease for h equal to eight that was found in the univariate regression. It is hard to find an economic explanation for a drop in the impact of a market uncertainty shock on silver volatility, which is followed by an increase again. However, the impact on volatility growth was solely significant at the 5 %, but not the 1 % significance level. The impulse response function increases until 57 days after the initial shock. The coefficient estimates remain at roughly the same level even thereafter. All assets have significant serial correlation coefficients for every h. However, volatilities for metals are specifically persistent, which explains the results from figure 38. A gradual decrease in the impulse response function after a couple of days is found for oil, the NASDAQ, and SP500. For gold, silver, and copper, the effects on volatility are very long-lasting. The impact of a market uncertainty shock on silver volatility gets insignificant more than 100 days after the initial shock.

Moreover, we cannot reject that $\gamma_{1,h}$ and $\delta_{1,h}$ are zero for all h. Hence, we find another difference between gold and silver. Economic policy uncertainty and geopolitical uncertainty impacted the growth of gold volatility when including market uncertainty and other controls in the regression. However, there is no impact on differenced silver volatility.

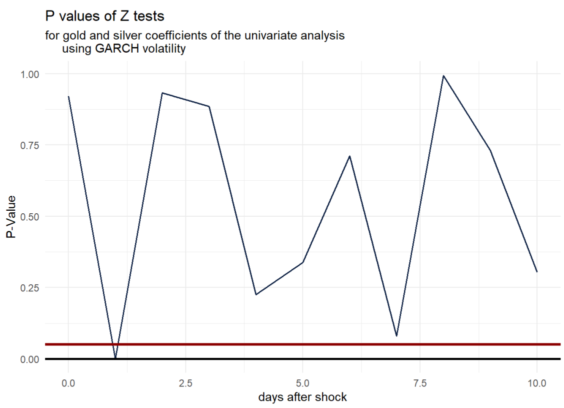


Figure 39

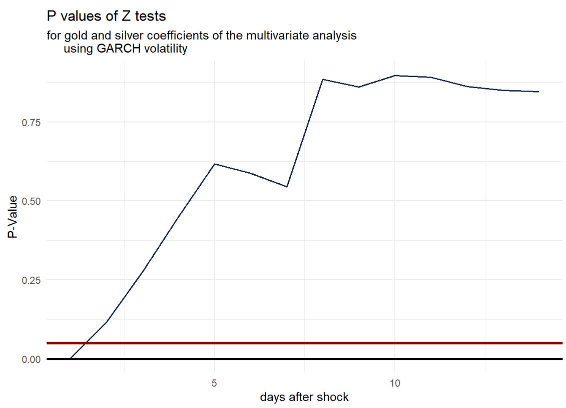


Figure 40

Graph 39 indicates that the p-values are below 0.05 for h=1. As the coefficient estimates of gold are smaller than those of silver, we conclude that shocks in the CBOE volatility index impact gold volatility less than silver volatility. We cannot reject the null hypothesis that the coefficients are the same for other h. Similarly, the coefficients of the multivariate regression are only significantly different from each other on the first day after the shock. It is interesting to note that the coefficient estimates of the $VMA(\infty)$ representation of the VAR model of gold are mostly bigger than the coefficient estimates of silver, as depicted in figure 20 and figure 38. However, the difference is not significant at the 5 % significance level for these days. Silver coefficients are solely smaller for the first day after the shock, but the difference is significant at the 5 % level on this day. Looking at the p-values of the Z tests of the multivariate models, solely the coefficients one day after the shock are significantly different from each other. When gold coefficient estimates are higher than silver coefficient estimates, we cannot reject the null hypothesis. Hence, gold volatility is impacted less than silver volatility by a shock in market uncertainty, but only for a short time.

We can reject the null hypothesis of the Chow-test when February 24^{th}, 2022 is selected as the break date. However, we fail to reject the null hypothesis when the end of the Great Recession is chosen. Hence, we find different breakpoints for gold and silver even though both are precious metals and closely correlated.

The findings of the univariate and multivariate regression show that silver volatility is expected to increase following a shock in the VIX as the coefficients are significantly different from zero when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. Unlike other metals considered in this paper, impacts on the growth of silver volatility can be solely found one day after the shock. The share of silver used for industrial purposes is higher than gold, as this precious metal is essential for medical technology. There is also demand for silver as a pure investment asset, as stated by O'Connor et al. (2015). The difference in the economic usage of this precious metal may explain these results.

5.2 Credit Spreads

As we want to ensure the robustness of our results, the proxy for market uncertainty is changed from the CBOE VIX to average credit spreads. Detailed information about this variable is provided in section 4.8. Previously, it was stated that the CBOE volatility index as a proxy for market uncertainty might have downsides, especially as it is calculated using SP500 index option prices. Let us assume that a market uncertainty shock occurs that is not or only weakly reflected in SP500 option prices. However, this shock causes the volatility of many other assets to increase. The CBOE VIX is a bad proxy for market uncertainty in such a case, as it cannot comprehend the fear in all markets. Naturally, the contrary can also be the case. Smaller market uncertainty shocks can disproportionately impact the CBOE volatility index, thereby overstating the reaction of market uncertainty. Hence, a second proxy for market uncertainty is included to check how robust the previous findings are.

The univariate regression with differenced asset return volatilities is the following

$$\Delta\sigma_{asset,t+h} = \alpha_h + \beta_h \cdot \widetilde{CS}_t + \gamma_{1,h} \cdot \Delta EPUI_t + ... + \gamma_{m,h} \cdot \Delta EPUI_{t-m} +$$

$$\delta_{1,h} \cdot \Delta GPRI_t + ... + \delta_{n,h} \cdot \Delta GRPI_{t-n} + \epsilon_{t+h}$$

$\widetilde{CS_t}$ indicates the residuals of an ARIMA(1,1,1) specification of logarithmic credit spreads. H is between 0 and 10.

The multivariate VAR(k) regression uses asset return volatilities as one of the response variables. The specification looks as follows.

$$\begin{pmatrix} log(\sigma_{asset,t}) \\ \Delta CS_t \\ log(EPUI_t) \\ log(GPRI_t) \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \\ \phi_{30} \\ \phi_{40} \end{pmatrix} + \begin{pmatrix} \phi_{1,11} & \phi_{1,12} & \phi_{1,13} & \phi_{1,14} \\ \phi_{1,21} & \phi_{1,22} & \phi_{1,23} & \phi_{1,24} \\ \phi_{1,31} & \phi_{1,32} & \phi_{1,33} & \phi_{1,34} \\ \phi_{1,41} & \phi_{1,42} & \phi_{1,43} & \phi_{1,44} \end{pmatrix} \begin{pmatrix} log(\sigma_{asset,t-1}) \\ \Delta CS_{t-1} \\ log(EPUI_{t-1}) \\ log(GPRI_{t-1}) \end{pmatrix}$$

$$+ ... + \begin{pmatrix} \phi_{k,11} & \phi_{k,12} & \phi_{k,13} & \phi_{k,14} \\ \phi_{k,21} & \phi_{k,22} & \phi_{k,23} & \phi_{k,24} \\ \phi_{k,31} & \phi_{k,32} & \phi_{k,33} & \phi_{k,34} \\ \phi_{k,41} & \phi_{k,42} & \phi_{k,43} & \phi_{k,44} \end{pmatrix} \begin{pmatrix} log(\sigma_{gold,t-k}) \\ \Delta CS_{t-k} \\ log(EPUI_{t-k}) \\ log(GPRI_{t-k}) \end{pmatrix} + \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \end{pmatrix}$$

As we have already pointed out in the section "Specification of regressions", the interpretation is that a one-unit shock in differenced credit spreads causes the volatility of the asset of interest to increase by the coefficient value times 100. Do not get confused that the units with which credit spreads are measured are already %. When we are referring to a one-unit increase, this means that credit spreads increase by 1 %.

5.2.1 Gold

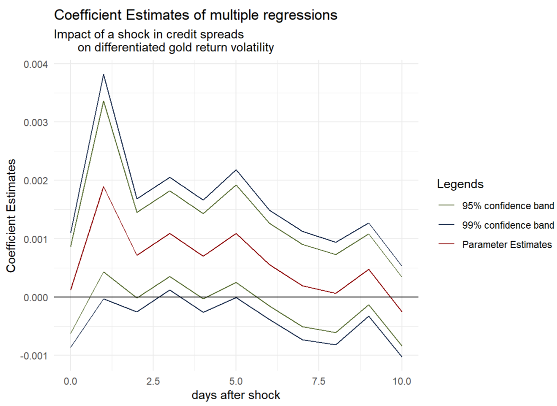


Figure 41

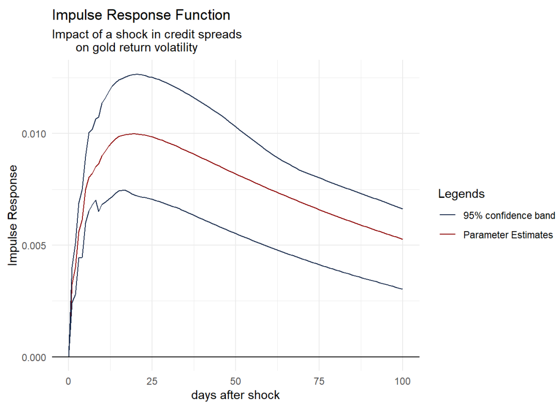


Figure 42

A 1 % shock or innovation in credit spreads is expected to increase differenced gold volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h equal to one at the 5 % significance level and for h equal to three and five at the 1 % significance level. The biggest coefficient estimate is found one day after the initial shock. The value is 0.00185. Interestingly, the coefficient estimate for h equal to one is bigger than the coefficient estimate for h equal to three. However, we can reject the null hypothesis that β_h is zero solely for h equal to three at the 1 % significance level. It is once again puzzling why the coefficient for h equal to two drops off and is not statistically significant. However, the coefficient estimates two and four days after the shock are positive this time and the 95 % confidence bands almost do not include zero. We can see that the coefficient estimates gradually decrease five days after the shock and we cannot find significant impacts on differenced gold return volatility anymore. The coefficient estimates in this subsection are higher than before when the CBOE volatility index was used as the market uncertainty proxy. The interpretation is that an exogenous 1 % increase in credit spreads impacts the growth of gold volatility more than a 1 % exogenous impact in the CBOE volatility index. The ratio of the biggest coefficient estimates of the regressions with credit spreads and the VIX as a market uncertainty proxy is 3.012. This ratio is calculated for other assets too. Then the results are compared and it is shown which assets are specifically sensitive to the selection of the market uncertainty proxy. Figure 42 shows that the shape of the impulse response function corresponds to the results from figure 20. The biggest coefficient is around 0.01. Hence, a one-unit shock in differenced credit spreads is expected to increase gold volatility by up to 1 %. However, it takes longer until that peak is reached compared with the impulse response of the previous sections. Furthermore, the monotony of the function is only altered once. The coefficient estimates 100 days after the initial shock are around half of the highest coefficient estimates of this function. This is in contrast to the results when the volatility index was used as a market uncertainty proxy.

Moreover, $\gamma_{1,h}$ is significant for h equal to one at the 1 % significance level and $\delta_{1,h}$ is significantly different from zero for h equal to zero at the 5 % significance level. Economic and geopolitical uncertainty maintains explanatory power for the growth of gold return volatility when we control for market uncertainty and other factors.

The results of the univariate and multivariate analysis indicate that gold volatility is expected to increase following a shock in credit spreads when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. In order to assess the reaction of gold volatility, the results are compared to the reaction of other assets.

5.2.2 SP500

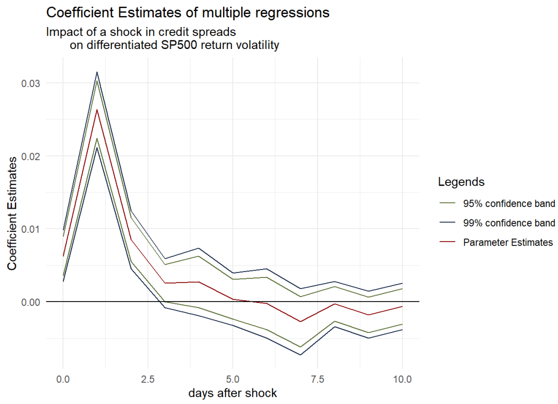


Figure 43

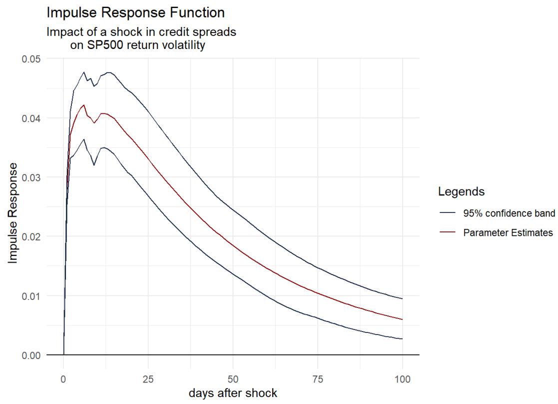


Figure 44

A 1 % shock or innovation in average credit spreads is expected to increase differenced SP500 return volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h between zero and two at the 1 % significance level. No significant impacts are found afterwards. β_0 for none of the univariate regressions for any asset are significantly different from zero so far. As GARCH-based conditional volatility is calculated, the results are not surprising. The conditional volatility is solely dependent on past values and the residuals of an ARIMA specification of credit spreads show no significant serial correlation. The highest coefficient estimate of the univariate regression with the growth of SP500 volatility as the dependent variable is 13.87 times the highest coefficient estimate of the regression with differenced gold volatility as the explained variable. The ratio of the biggest coefficients of the univariate models with credit spreads as the independent variable to the one with the VIX as the explained variable is 2.644. This confirms the intuition that SP500 volatility responds more to changes in the VIX relative to the impacts of a shock in credit spreads, compared with gold. Figure 44 displays a sharp increase in SP500 volatility within the first two days. A one-unit shock in differenced credit spreads is expected to increase SP500 volatility by up to 4.2 %. Hence, the growth in gold volatility is not only impacted less than the growth in SP500 volatility in absolute terms, but gold volatility is also less affected than SP500 relative to its size. The biggest impact is approximately half the value of the biggest impact of the impulse response function when the Volatility Index is used as a market uncertainty proxy. The ratio for gold is approximately one. This finding further underlines the close relationship between the VIX and the SP500. The coefficients of the impulse response function move down and up quickly after the global maximum of the function is reached. Then the coefficient estimates gradually decrease. As we have already pointed out previously, the decay is faster than the decay of the metals considered in this paper as the autocorrelation functions of the metals indicate specific long-lasting persistence.

We can reject the null hypothesis that $\gamma_{1,h}$ is zero for h equal to zero. The null hypothesis that $\delta_{1,h}$ is zero for h = 0 is rejected at the 5 % significance level. These results are consistent with the findings using the VIX as the explanatory variable.

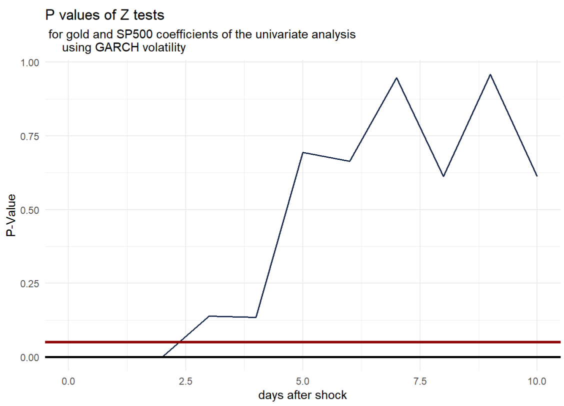


Figure 45

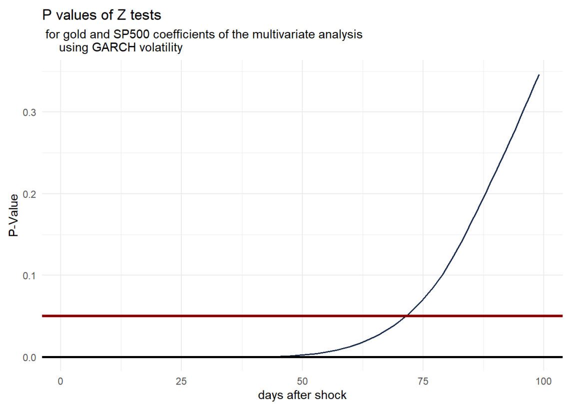


Figure 46

Figure 45 indicates that the p-values of the Z tests are below 0.05 for several h. As the coefficient estimates of gold are smaller than those of the SP500, we conclude that shocks in the credit spreads impact gold volatility less than SP500 volatility. The confidence bands in the graphs show that these results are not a surprise. Furthermore, the coefficients of the multivariate VMA representation are significantly different from each other for approximately 70 days.

The results of the univariate and multivariate analysis indicate that SP500 volatility is expected to increase following a shock in credit spreads as the coefficients are significantly different from zero when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. According to our results, gold volatility is less affected than SP500 volatility by credit spread shocks. These results are consistent with the findings in subsection 6.1.2. A difference is that SP500 volatility reacts less to shocks in the credit spreads relative to the reaction of shocks in the CBOE volatility index compared with gold volatility.

5.2.3 NASDAQ

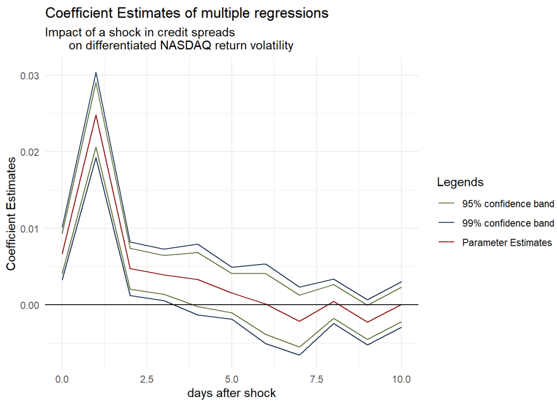


Figure 47

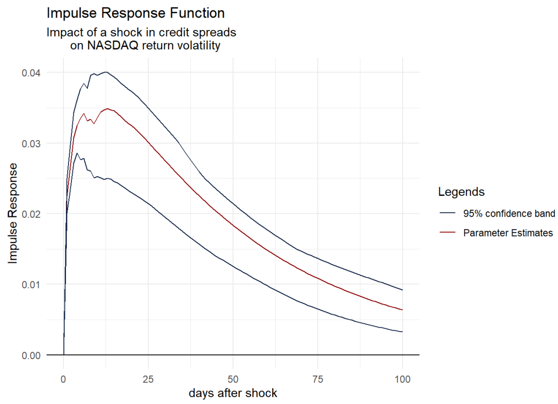


Figure 48

A 1 % shock or innovation in corporate bond yield spreads is expected to increase differenced copper return volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that the coefficient β_h is zero for h between zero and three at the 1 % significance level. The coefficient estimates fluctuate around zero afterward. The coefficients are not statistically significant at the 1 % level anymore. The autocorrelation function of the residuals of an ARIMA process of credit spreads indicates that no significant serial correlation remains. The coefficient estimates peak one day after the shock. The biggest value is around 0.02481, which is slightly below the highest coefficient estimate of the regression with differenced SP500 volatility and 13.07 times the peak coefficient estimate of gold. The ratio of the biggest coefficients of the univariate models with credit spreads as the independent variable to the one with the VIX as an independent variable is roughly 2.41. Differenced NASDAQ volatility is more sensitive to changes in the VIX relative to changes in credit spreads compared with gold. Even though the CBOE volatility index is measured using SP500 option prices, the unconditional correlation between SP500 returns and NASDAQ returns is high. This result explains the high sensitivity to changes in the VIX compared to shocks in credit spreads. The coefficient is negative and significant at the 5 % significance level nine days after the initial market uncertainty shock. Figure 48 depicts that the highest impact of an innovation in market uncertainty on NASDAQ volatility is found after twelve days following a quick increase. In figure 32, the peak is earlier. A one-unit shock in differenced credit spreads is expected to increase NASDAQ volatility by up to 3.5 %. Furthermore, the peak value of the impulse response function with the VIX as a market uncertainty proxy is 0.065. It is 0.035 this time, which is a decrease of 46 %. Note that the peak values for gold are roughly the same. Furthermore, the coefficients are significantly different from zero 100 days after the initial market uncertainty shock. However, at a lower level than during the period when the impulse response function peaked.

We can reject the null hypothesis that $\gamma_{1,h}$ and $\delta_{1,h}$ are zero for h=0. The coefficient measuring the impact of an exogenous shock in the geopolitical risk index is solely significant at the 5 % significance level in the previous subsection using the VIX as a market uncertainty proxy. Independent of the selection of the market uncertainty proxy, the GPRI, and EPUI have explanatory power for the growth of NASDAQ volatility.

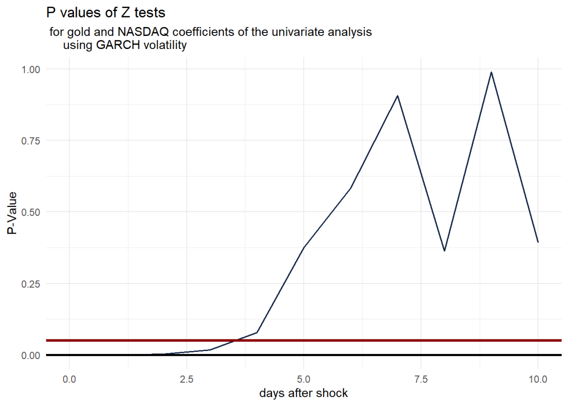


Figure 49

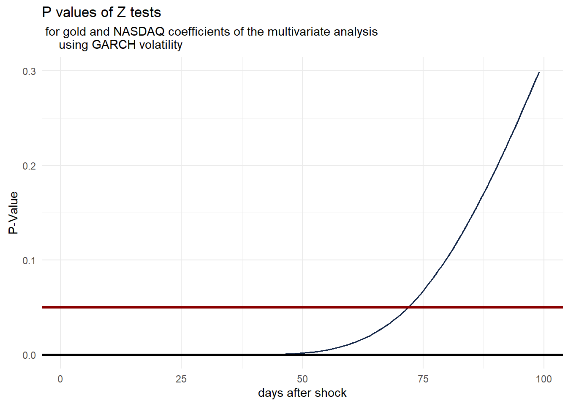


Figure 50

Figure 49 indicates that the p-values are below 0.05 for h between zero and three for the univariate regression and for h between 0 and 69 for the coefficients of the impulse response function. Hence, we conclude that shocks in credit spreads impact gold and NASDAQ volatility differently.

The results of both the univariate and multivariate regressions indicate that NASDAQ volatility is expected to increase following a shock in credit spreads as the coefficients are significantly different from zero when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. Moreover, both models indicate that gold volatility is impacted less than NASDAQ volatility by an increase in credit spreads. Because of its high correlation with the SP500, NASDAQ volatility is more sensitive to shocks in the CBOE volatility index relative to its peak reaction to shocks in credit spreads compared to the response of the volatility of gold returns.

5.2.4 Oil

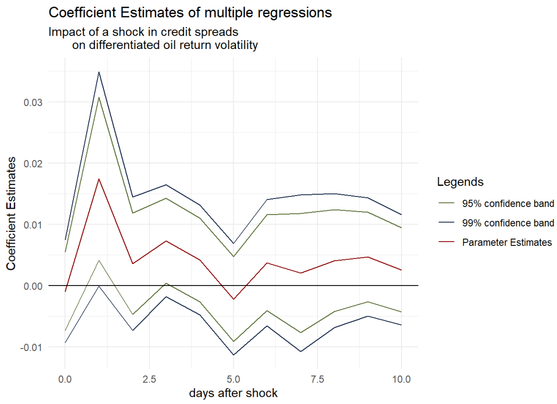


Figure 51

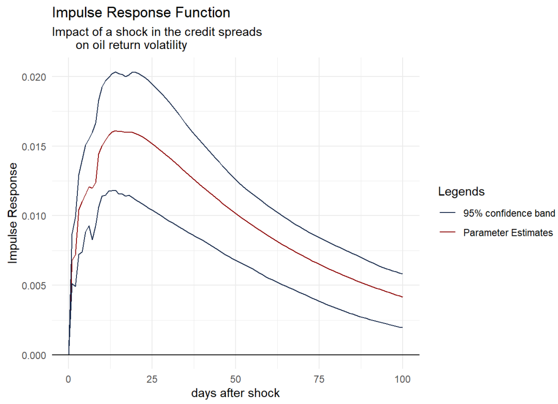


Figure 52

A 1 % shock or innovation in the spreads is expected to increase differenced oil return volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h equal to one and three at the 5 % significance level. We cannot reject the null hypothesis that β_1 is zero at the 1 % significance level, even though it is close. The value of the lower 99 % confidence band for h equal to one is slightly below zero. The coefficient estimates drop sharply two days after the initial shock before it increases quickly again. Unlike regressions with the growth of NASDAQ and SP500 volatility as the explained variable, the contemporaneous effect is not significant. The biggest coefficient estimate is 0.0174, which is 8.712 times the peak coefficient estimate of the regression with differenced gold volatility. The ratio of the biggest coefficient estimate of the univariate model with credit spreads as the independent variable to the biggest estimate of regression with the VIX as the independent variable is approximately 4.88, which is the highest ratio so far. Hence, crude oil is relatively sensitive to changes in the market uncertainty proxy compared to the reaction of the differenced volatility of other assets. Figure 52 indicates that it takes comparably long until innovations in credit spreads reach their highest impact on oil volatility. A one-unit shock in differenced credit spreads is expected to increase oil volatility by up to 1.6 %. The biggest impact is 60 % higher than the biggest impact on gold volatility. Looking at the confidence bands, we expect that it is a close case whether we can reject the null hypothesis of the Z test. Furthermore, the decay is faster when credit spreads are used as market uncertainty proxies even though the effects are significantly different from zero 100 days after the initial shock.

We cannot reject the null hypothesis that $\gamma_{1,h}$ or $\delta_{1,h}$ is zero for any h. This corresponds to the results found in the previous subsection and underlines that the findings are robust to the selection of the proxy of market uncertainty.

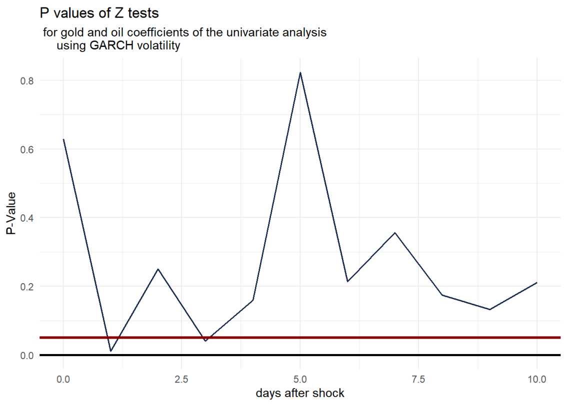


Figure 53

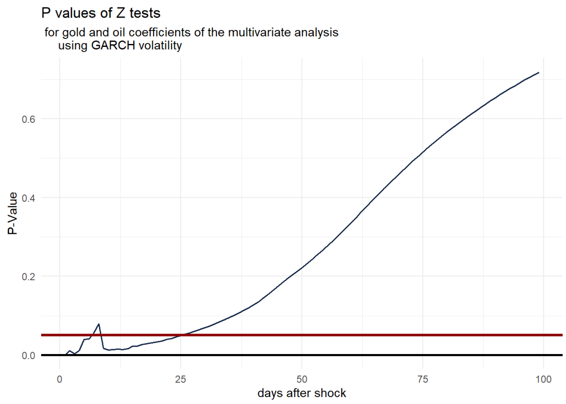


Figure 54

Figure 53 indicates that the p-values of Z tests are below 0.05 for h equal to one and three. The coefficients from the second day after the initial market uncertainty shock are not significantly different from each other. Shocks in the credit spreads impact gold volatility less than oil volatility as the coefficient estimates of gold are also smaller than those of oil. The figure displaying the p-values of Z tests from the coefficients of the multivariate regressions shows that the graph is below 0.05 for h between 0 and 28 with some exceptions. The shape of the impulse response function outlines that there is a short period between four and eight days after the shock when the growth of the function decreased but is still positive. The impulse response function with gold volatility increases faster and catches up during that period t. We cannot reject the null hypothesis that the coefficients are the same during that period.

The results of both the univariate and multivariate regressions point out that oil volatility is expected to increase following a shock in credit spreads as the coefficients are significantly different from zero when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. The effects on oil return volatility are different than gold. We can reject the null hypothesis that oil and gold coefficients are the same for the first couple of days after the shock for the multivariate analysis. To sum up, gold volatility is less affected than oil volatility by credit spread uncertainty shocks according to our results. The findings are similar to those with the CBOE volatility index as the market uncertainty proxy. Hence, we conclude that the previously found results are robust to the selection of the market uncertainty proxy.

5.2.5 Copper

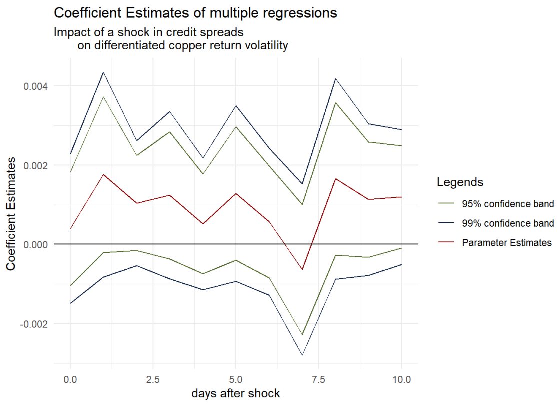


Figure 55

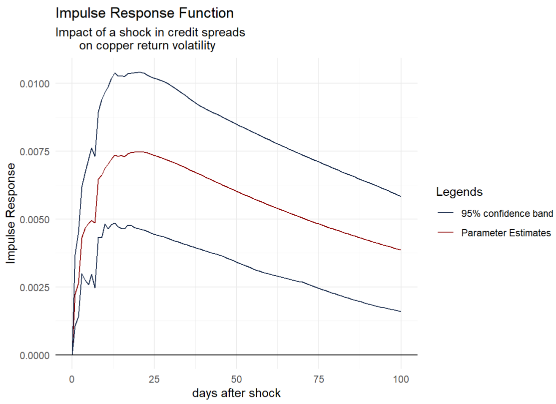


Figure 56

A 1 % shock or innovation in the average credit spreads is expected to increase differenced copper return volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We cannot reject the null hypothesis that β_h is zero at the 1 % significance level. This is the first asset whose growth in conditional volatility does not significantly react to shocks in corporate yield spreads. All coefficient estimates for the first ten days are positive with one exception. We almost reject the null hypothesis at the 5 % significance level for some coefficients like β_1, β_2, and β_{10}. Most coefficient estimates are close to the estimates of the regressions using the growth in gold volatility as the explained variable. However, the confidence bands of the regression with differenced conditional gold volatility are narrower. Hence, we can reject the null hypothesis that the coefficients are zero, which is not possible for the regression with copper. It is tested whether coefficients are also different from each other later. The ratio of the biggest coefficient estimates of the univariate model with credit spreads as the independent variable to the coefficient estimates of a regression with the VIX as the independent variable is 2.09. This is lower than for SP500 and the NASDAQ. However, these results do not automatically imply that the coefficients of the multivariate regressions using copper volatility are not significantly different from zero. The impacts of a market uncertainty shock on the growth of the volatility of an asset can be insignificant, but the impact on the volatility of this asset is significantly different from zero. Figure 56 outlines that this is the case here, as the upper and lower bound of the 95 % confidence bands never include zero. A one-unit shock in differenced credit spreads is expected to increase copper volatility by up to 0.75 %. The coefficients of the multivariate model are significant for all h. The biggest impact on copper volatility is 0.0075 which is 21.05 % less than the biggest impact when the CBOE VIX is used as a market uncertainty proxy. It is also 25 % lower than the biggest impact on gold volatility using credit spreads as a market uncertainty proxy. It is interesting to see whether the volatility of copper is impacted significantly less than gold volatility as it would show that the reaction of gold volatility to market uncertainty shocks is not unique. As already pointed out, copper volatility has a high serial correlation which is why the decrease of the impulse response function is rather slow.

We can reject the null hypothesis that $\gamma_{1,h}$ is zero for h equal to zero. We cannot reject the null hypothesis that $\delta_{1,h}$ is zero at the 5 % level. The very same results are also found when the CBOE VIX is used as a market proxy and shows that the main takeaways are independent of the choice. Economic policy uncertainty still positively impacts the growth of copper volatility when controlling for market uncertainty and other factors.

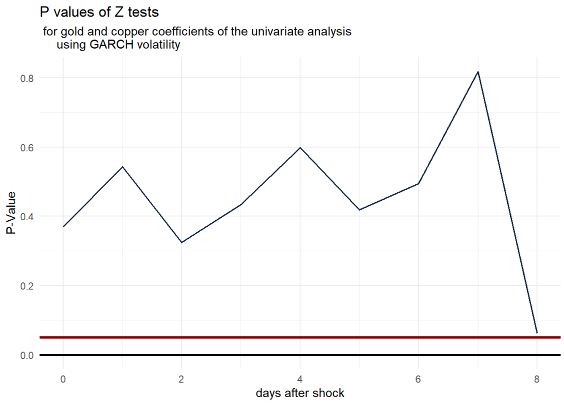


Figure 57

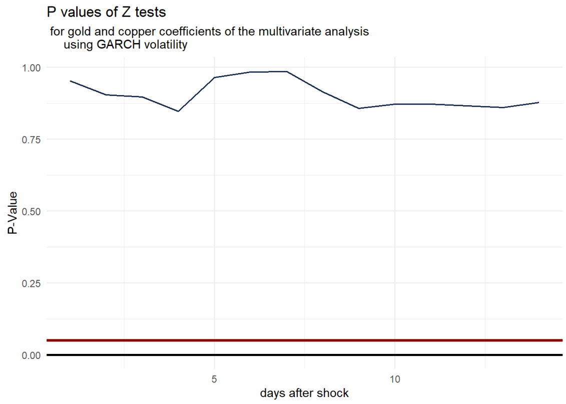


Figure 58

The graphs indicate that the p-values of Z tests are never below 0.05 for the univariate and multivariate analysis. Hence, the volatility of copper reacts similarly to shocks in market uncertainty. Thus, gold volatility does not have a unique reaction to shocks in credit spreads. However, we have not found another asset whose volatility is significantly less impacted in times of market uncertainty.

The results of the multivariate regression indicate that copper volatility is expected to increase following a shock in credit spreads as the coefficients are significantly different from zero at the 5 % significance level when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. The univariate analysis finds that the growth of copper volatility is not significantly impacted by shocks in this market uncertainty proxy. Hence, whether the growth of copper volatility is significantly impacted by market uncertainty shock depends on the selection of the proxy. The impacts on gold and copper volatility are not significantly different from each other for both proxies. This result is independent of the choice of the market uncertainty proxy.

5.2.6 Silver

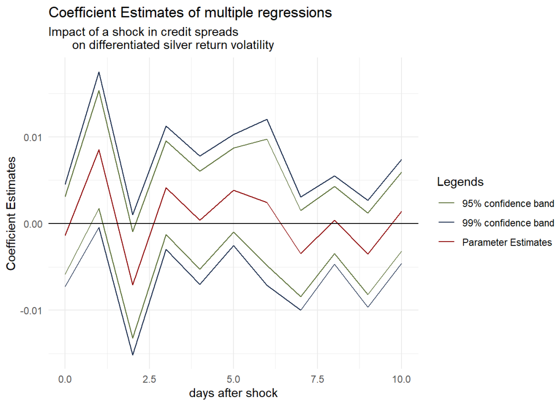


Figure 59

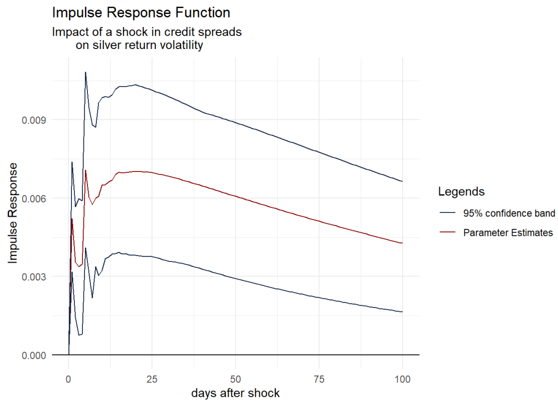


Figure 60

A 1 % shock or innovation in average credit spreads is expected to increase differenced silver return volatility by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h equal to one and two at the 5 % significance level. Similar to the coefficient estimates of the univariate regression with the VIX as the market uncertainty proxy, the only significant and positive coefficient is β_1. The ratio of the two biggest coefficient estimates of the univariate regressions with different market uncertainty proxies is 2.517, which is in the middle of the pack compared with the ratios of other assets. Moreover, the biggest coefficient estimate is four times that of the regression with differenced silver volatility as the dependent variable than with gold volatility growth as the explained variable. A unique and puzzling impact is found two days after the market uncertainty shock. The coefficient estimate is negative and we can reject the null hypothesis that the coefficient is zero at the 5 % significance level. Gradual declines are observed for other assets. It is worth noting that the first lag of the autocorrelation function of differenced silver volatility is significant and negative. While other assets like copper and oil have similar characteristics, the magnitude of this correlation coefficient is unique among all assets considered in this paper. Hence, a quick increase in the growth of silver volatility is typically followed by a strong decrease. The economic interpretation is that silver volatility reacts positively to market uncertainty shocks. Its volatility is corrected downwards the day after. Figure 60 shows the impacts of a shock in market uncertainty on silver volatility. It confirms the findings from figure 59 as a quick increase is followed by a decrease. Despite the significant negative increase, the coefficients are significant and positive at the 5 % significance level. A one-unit shock in differenced credit spreads is expected to increase silver volatility by up to 0.7%. The impulse response function moves up and down afterward until its peak is reached after 15 days. Silver volatility has the special characteristic that the highest impact is reached after comparably few days when the VIX is used as a market uncertainty proxy. Silver volatility loses this peculiarity when we change the market uncertainty proxy. The biggest impact on silver volatility is 16.6 % lower compared to the impact of the VIX as the market uncertainty proxy. There is essentially no change in the peak coefficient estimates for the analysis with gold when the market proxy is adapted. This result confirms that gold volatility is particularly sensitive to changes in average credit spreads relative to a shock in the VIX. The peak value of silver is also 25 % lower than the peak value of gold. Hence, we are questioning whether the volatility of silver reacts significantly less to changes in market uncertainty. Hence, we calculate the p-values of the Z tests. However, the reaction of differenced silver volatility to exogenous shocks in the GPRI and EPUI is analyzed first. We cannot reject the null hypothesis that $\gamma_{1,h}$ and $\delta_{1,h}$ is zero at the 5 % significance level for all of the h different regressions. This is in line with the previous finding according to which silver volatility is insensitive to exogenous changes in geopolitical or economic risk when controlling for financial market risk.

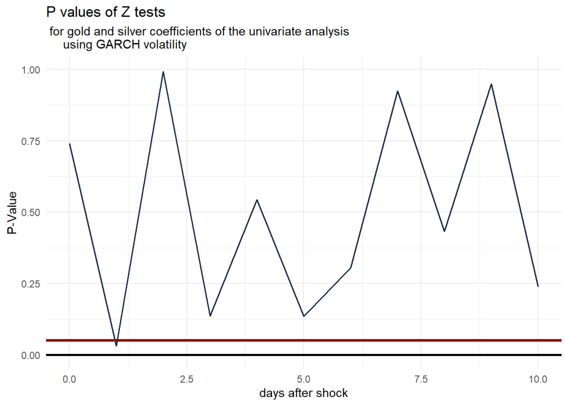


Figure 61

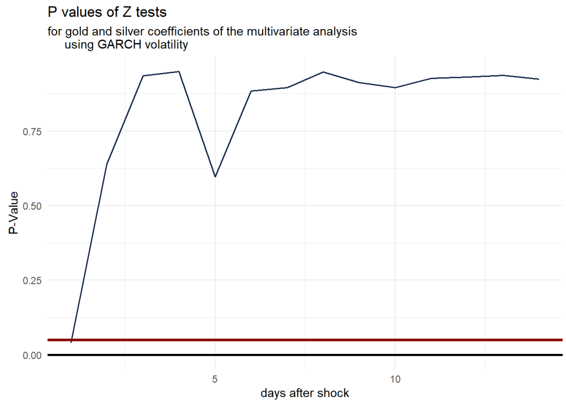


Figure 62

The graph indicates that the p-values of Z tests for gold and silver coefficients are below 0.05 for h equal to 1. As the coefficient estimates of gold are smaller than those of silver, it is concluded that shocks in the CBOE volatility index impact the growth in gold volatility less than the growth in silver volatility. For h equal to two, the coefficient of the univariate regression with differenced silver volatility as the explained variable is significant and negative. We can not reject the null hypothesis that the coefficients of the regressions with differenced gold and silver volatility are the same for the second day after the shock. Most coefficient estimates for the multivariate regression with silver volatility are bigger than for the multivariate regression with gold volatility. However, we can solely reject the null hypothesis that the coefficients are the same for h equal to one. The impulse response function for gold volatility is below the impulse response function for silver one day after the shock, as it takes a couple of days until the coefficient estimates of gold are bigger than those of silver. However, we can reject the null hypothesis that the coefficients are the same on the first day. We conclude that shocks in the CBOE volatility index impact gold volatility less than silver volatility, but solely for a very short time period until the impacts are not distinguishable anymore.

The results of both the univariate and multivariate regressions show that silver volatility is expected to increase following a shock in credit spreads as the coefficients are significantly different from zero when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null that the coefficients for gold and silver are the same. The results do not depend on the selection of the market proxy. We have seen that differenced gold volatility is impacted less solely on the first day after the shock independent of the choice of the proxy. Furthermore, we cannot reject the null hypothesis that the coefficients are the same for higher h.

6 Impacts of uncertainty shocks on volatility by Garman and Klass

The previous sections show that GARCH conditional volatility has some downsides. For example, it takes a while until the conditional volatility closes up to volatility regime changes. The underlying volatility changes to another level immediately following certain events. However, it takes a while until the conditional volatility adjusts to a regime change as GARCH takes observations and values of previous days into account. High weights on the residuals of the mean model with higher lags are found when the GARCH models are transformed into $ARCH(\infty)$ models. This decreases the capability of GARCH models to react to sudden changes.

Hence, another way to calculate volatility is chosen, which was proposed by Garman and Klass (1980). Their goal was to construct a volatility estimate based on the most available data in the market, which are open, close, high, and low prices. The formula looks as follows

$$\sigma_t^2 = 0.17 \cdot \frac{(O_t - C_{t-1})^2}{f} + 0.83 \cdot \frac{(H_t - L_t)^2}{(1-f) \cdot 4 \cdot ln(2)}$$

, where O_t is the daily opening price, C_{t-1} is the closing price of the previous day, H_t is the maximum price of a trading day, and L_t is the minimum price of the trading day. f indicates the fraction of the day when trading is not possible. Here, it was decided to calculate f based on the core trading sessions of the New York Stock Exchange, which are from 9:30 am to 4:00 pm, according to New York Stock Exchange (2023). Opening, closing, high and low prices are provided by Yahoo Finance. Garman and Klass argue that their volatility estimate is superior to others as theirs is more efficient. The downside of this approach is that the volatility from one day to another can have high deviations. Conditional GARCH volatility develops more smoothly over time. Furthermore, using solely four intraday observations can cause problems. As a result, the deviation from the true underlying volatility can be high. On the other hand, Realized Variance estimates are consistent, according to Barndorff-Nielsen and Shephard (2002). Our sample size is large as it includes daily observations from 2000 to 2023. Getting intraday high-frequency prices for almost 23 years for every asset is challenging. It is therefore decided to use the volatility proposed by Garman and Klass, because of the easy accessibility of the data.

The objective of this section is to check the robustness of the previous results. We want to answer whether the main findings and takeaways are robust to changes in the way volatility is calculated.

6.1 Volatility Index

The following regression is run in this subsection.

$$\Delta\sigma_{asset,t+h} = \alpha_h + \beta_h \cdot \widetilde{VIX_t} + \gamma_{1,h} \cdot \Delta EPUI_t + ... + \gamma_{m,h} \cdot \Delta EPUI_{t-m} +$$
$$\delta_{1,h} \cdot \Delta GPRI_t + ... + \delta_{n,h} \cdot \Delta GRPI_{t-n} + \epsilon_{t+h}$$

, where $\Delta\sigma_{asset,t+h}$ is the differenced volatility of a prespecified asset. The number of lags m and n that are included in the model is decided based on the adjusted R^2. Depending on the results of the White and Breusch Pagan test, heteroskedasticity robust standard errors are used. Furthermore, heteroskedasticity and autocorrelation corrected Newey West standard errors are calculated given the results of the Ljung Box test.

The impacts of a shock in the volatility index on the newly calculated volatility of assets are graphically displayed in figure 63 to 68. The most obvious difference to the findings of the previous sections is the immediate positive impacts. Figure 63 shows that the biggest impact of a shock in the volatility index on differenced gold return volatility occurs on the same day. No significant coefficients can be found afterward. The smallest coefficient estimate is found for the first day after the biggest shock. This is similar to the results of the regression with GARCH-based conditional volatility. Furthermore, the biggest impact of a shock in the VIX is 25 times the value when Garman and Klass volatility instead of GARCH volatility is used.

Figure 64 displays how differenced silver volatility reacts to exogenous changes in the VIX. The main difference to the coefficient estimates of gold is that the contemporaneous impact is roughly 33 % higher. No significant effect on differenced silver volatility is found after the first day. Note that this does not mean that volatility is on the same level as before the shock after one day. The autocorrelation function in the appendix indicates that Garman-Klass volatilities are also persistent, even though less than the GARCH volatilities. The biggest impact of the shock is 5.71 times the peak impact of using GARCH volatility. However, we cannot reject the null hypothesis of the Z test that the coefficient of the regressions using gold and silver volatility are the same. This is different from the case using GARCH volatility. Hence, the way volatility is calculated changes whether the growth in gold volatility is significantly less sensitive to changes in volatility index shocks than the growth in silver volatility.

Figure 65 depicts the impact on differenced copper volatility. The contemporaneous coefficient estimate is statistically significantly different from zero at the 1 % significance level. The biggest coefficient estimate is approximately 33 % lower than the biggest coefficient estimate of the regression with gold coefficients. However, the coefficients are not significantly different from each other. Furthermore, the coefficient is almost significantly different from zero and negative at the 5 % level on the day after the initial shock.

The biggest coefficient estimate is roughly 13.5 times the peak coefficient estimate of the regression when GARCH-based volatility is used. The null hypothesis that copper and gold coefficients are the same cannot be rejected at the 5 % significance level. Hence, the growth of copper volatility is significantly less sensitive to changes in market uncertainty compared with gold, even though the coefficient estimates are smaller.

Figure 66 shows how the growth in oil volatility reacts to exogenous changes in the VIX. The main difference to the coefficient estimate plot of gold is that the biggest impact is 2.08 times the peak impact on the growth of gold volatility. The coefficient estimate is negative and the coefficient is significantly different from zero at the 5 % level one day after the shock. Hence, we expect a quick increase in oil volatility on the day of the shock, which is followed by a significant decrease. However, oil volatility is still not at its initial level, as the negative coefficient is approximately a third of the positive contemporaneous coefficient in absolute values. The latter is also significant at the 1 % significance level. The impact of a shock in the volatility index on the growth of oil volatility is 7.14 times the impact when oil volatility is calculated using high, low, open, and close prices instead of GARCH-based conditional volatility. The impact two days after the initial shock is positive and significant at the 5 % level. No significant impacts are found afterward. We can reject the null hypothesis that gold and oil coefficients are the same for h equal to one and three. When oil coefficients are negative and significant for h equal to two, no significant difference is found. Hence, growth in gold volatility is significantly less sensitive to shocks in the VIX than growth in oil volatility.

Figure 67 indicates the coefficient estimates of a regression on differenced NASDAQ volatility. There is a contemporaneous positive significant impact at the 1 % significance level and a negative significant impact for h equal to two at the 5 % significance level. The biggest coefficient estimate of the regression with differenced NASDAQ return volatility is 86 % higher than the highest coefficient estimate of the regression with differenced gold returns. The coefficient estimate is 2.8 the coefficient estimate of the same regression using conditional GARCH volatility. VIX market uncertainty shocks do not lead to permanent volatility regime changes as there is a significant negative coefficient. As a result, the decrease is not small and gradual but sharp and statistically significant after two days. We can reject the null hypothesis that the coefficient of the growth of NASDAQ and the coefficient of the growth of gold volatility are the same for the contemporaneous impact. Hence, differenced gold volatility is less sensitive to exogenous VIX market uncertainty shocks.

Last, we analyze the differenced SP500 return volatility. The immediate effect is significantly different from zero at the 1 % level. All other coefficient estimates are negative. The coefficient five days after the shock is even significantly different from zero at the 5 % level. The coefficient estimate for h equal to zero is 91 % higher than the one for gold. Moreover, this coefficient estimate tripled when we switched from GARCH volatility to the volatility estimate by Garman and Klass. We can also reject the null hypothesis that the β coefficients of the regressions with differenced gold and SP500 volatility as explained variables are the same.

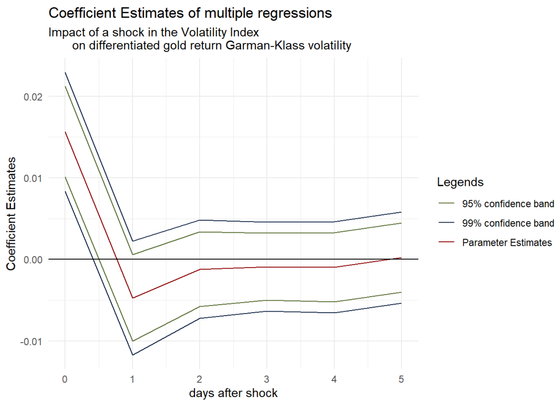
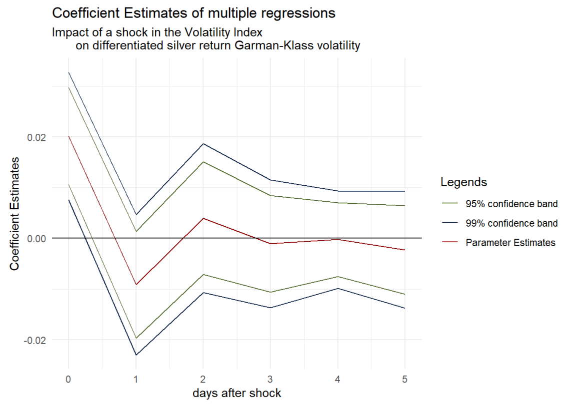


Figure 63



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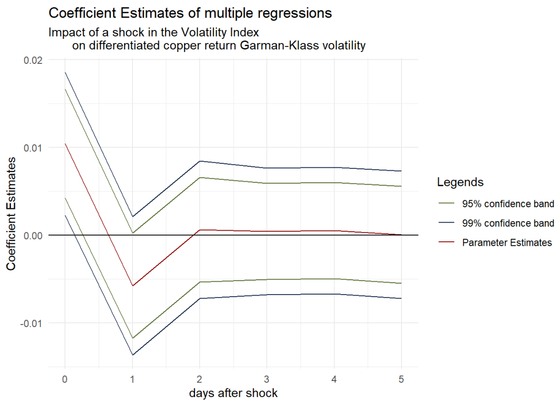

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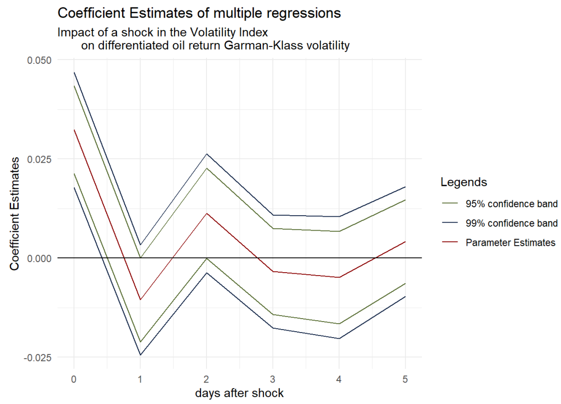


Figure 66

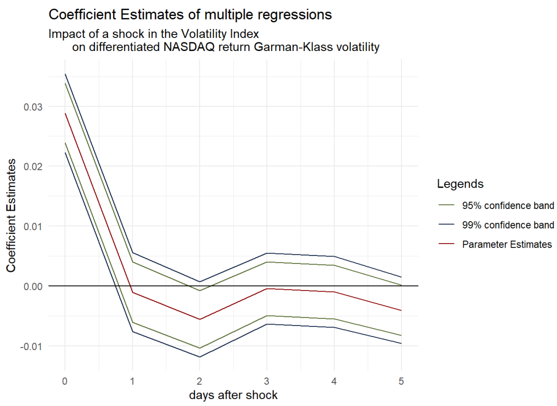


Figure 67

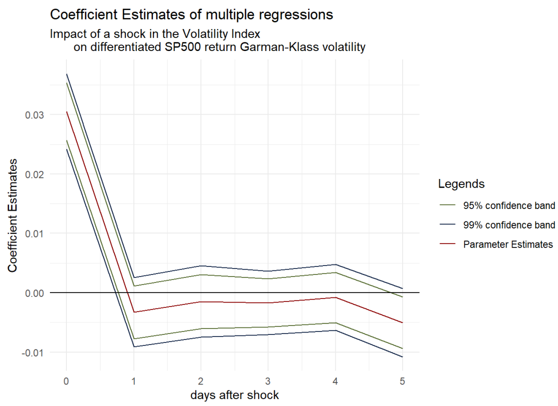


Figure 68

The graphs below indicate the impulse response function of a 1 % shock in the volatility index on asset volatility. Therefore, a VAR(k) model is transformed into a $VMA(\infty)$ model specification. k is decided based on the AIC. The VAR(k) looks as follows.

$$\begin{pmatrix} log(\sigma_{asset,t}) \\ log(VIX_t) \\ log(EPUI_t) \\ log(GPRI_t) \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \\ \phi_{30} \\ \phi_{40} \end{pmatrix} + \begin{pmatrix} \phi_{1,11} & \phi_{1,12} & \phi_{1,13} & \phi_{1,14} \\ \phi_{1,21} & \phi_{1,22} & \phi_{1,23} & \phi_{1,24} \\ \phi_{1,31} & \phi_{1,32} & \phi_{1,33} & \phi_{1,34} \\ \phi_{1,41} & \phi_{1,42} & \phi_{1,43} & \phi_{1,44} \end{pmatrix} \begin{pmatrix} log(\sigma_{asset,t-1}) \\ log(VIX_{t-1}) \\ log(EPUI_{t-1}) \\ log(GPRI_{t-1}) \end{pmatrix}$$

$$+ ... + \begin{pmatrix} \phi_{k,11} & \phi_{k,12} & \phi_{k,13} & \phi_{k,14} \\ \phi_{k,21} & \phi_{k,22} & \phi_{k,23} & \phi_{k,24} \\ \phi_{k,31} & \phi_{k,32} & \phi_{k,33} & \phi_{k,34} \\ \phi_{k,41} & \phi_{k,42} & \phi_{k,43} & \phi_{k,44} \end{pmatrix} \begin{pmatrix} log(\sigma_{asset,t-k}) \\ log(VIX_{t-k}) \\ log(EPUI_{t-k}) \\ log(GPRI_{t-k}) \end{pmatrix} + \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \end{pmatrix}$$

Figure 69 indicates the case when gold volatility is used. Immediately after the shock in market uncertainty, volatility increased sharply, followed by a more gradual growth. The coefficients get statistically significant two days after the initial shock. A 1 % exogenous increase in the VIX is expected to increase Garman-Klass gold volatility by up to 0.0003 %. There is a drop in the impulse response function after seven days. The impacts get statistically insignificant for a short period before they are significant again. The impulse response function gradually decreases afterward. The peak impact is $\frac{1}{31}$ times the impact of the case when GARCH volatility is used. It is found around the same time after the shock occurred. Based on the results in figure 63 and 69, the impacts on the growth of gold volatility are higher, but the effects on gold volatility are lower when volatility is calculated based on the idea by Garman and Klass. Furthermore, the autocorrelation of Garman and Klass volatility of gold is lower, even though statistically significant for up to 100 lags. This causes the impulse response to decrease faster compared to the case in figure 20. The coefficients of the impulse response function do not get insignificant for $9 \leq h \leq 100$.

Figure 70 shows the results when silver volatility is analyzed. The effects are significant from the very first day on. The function increases for the first four days. The biggest growth occurs on the very first day after the innovation. Then, the coefficients decrease sharply for eight days. The growth stays negative but is smaller in absolute terms compared to the initial increase with some exceptions. A 1 % exogenous increase in the VIX is expected to increase Garman-Klass silver volatility by up to 0.00063 %. Except for five to nine days after the shock, the coefficients are significantly different from zero at the 5 % significance level. The peak impact is roughly 100 % higher than the one of gold. We can reject the null hypothesis that the coefficients of the regression with gold and silver volatility are the same for h equal to four. Hence, gold volatility is impacted less than silver volatility by a VIX market uncertainty shock using Garman and Klass volatility.

Figure 71 shows the impulse response function of a shock in the VIX on copper return volatility. The coefficients increase seven days until the effects drop off and gradually decrease with the exception of h between 10 and 14. The effects are not significantly different from zero 9, 10, and 91 to 100 days after the shock. The peak coefficient estimate is 68 % bigger than for the regression with gold volatility. Once again, we cannot reject the null hypothesis that the coefficients of the regression with gold and copper volatility are significantly different from each other for any h. The biggest impact of the impulse response function is 18 times the impact when conditional GARCH volatility is used.

Figure 72 displays that the coefficients of the impulse response function do not get insignificant for the first 100 days after the shock. An immediate significant increase is followed by up and down movement of the impulse response function until the coefficients gradually decrease. The biggest coefficient estimate is 5.31 times the one from the impulse response function of gold. All of the coefficients for the first 100 days of the regression with oil volatility are significantly different from the coefficient of the regression with gold volatility. The peak impact is 11.76 times the impact when GARCH volatility is used. It may be confusing why the impulse response function does not evolve as smoothly as previously. For example, visually analyzing the impulse response function is almost impossible for h between five and ten, because of the quick up and down movement. Economically, it is not clear why the discrepancy in the impacts nine to ten days after the shock should be that different, as we expect a smooth decrease after the peak impact is reached. Previously, the downsides of conditional GARCH volatility were discussed. The fact that it takes residuals of an ARIMA process of theoretically infinite days into account also has its upsides. The reason is that outliers on one day have a smaller impact on conditional volatility. Garman and Klass volatility does not have that feature, which is why we can see a quicker reaction to the shocks. However, this also causes quick up-and-down movement in the impulse response function which is not economically intuitive. Furthermore, the question arises why high fluctuations in the impulse response function stop at some point. This is caused by the way a VAR(k) model is transformed into a VMA(∞) model. Hence, some of the characteristics of this impulse response function are questioned, as we would expect that the underlying, true impacts of a shock in market-wide uncertainty on oil volatility look different.

Figure 73 shows the impulse response of a shock in the VIX on NASDAQ return volatility. Compared with the functions of the other assets, the coefficient estimates increase even faster, as the global maximum is immediately reached. There is a negative trend until the effects are not statistically significantly different from zero anymore, which is 79 days after the initial shock. The biggest impact is five times the peak impact of a shock in the market uncertainty proxy on gold volatility, although the effects get insignificant earlier. The biggest coefficient estimate is 40.626 times the one when GARCH volatility is used. We can reject the null hypothesis that the coefficients are the same for the first 36 days after the shock.

Last, figure 74 displays the effects on SP500 return volatility. The shape of the graph looks similar to the one in figure 73. The peak impact is 0.00165 % and occurs immediately after the shock in the VIX. The coefficient estimates decrease afterward. However, one difference is that all coefficients are significantly different from zero at the 5 % level. The biggest impacts are 5.3 times the maximum value of the impulse response function of gold volatility. Furthermore, the peak coefficient estimate of the regression using SP500 volatility is 5.88 times the coefficient estimate when GARCH volatility of assets is plugged into the regression. We reject the null hypothesis of the Z test for the h between 0 and 84.

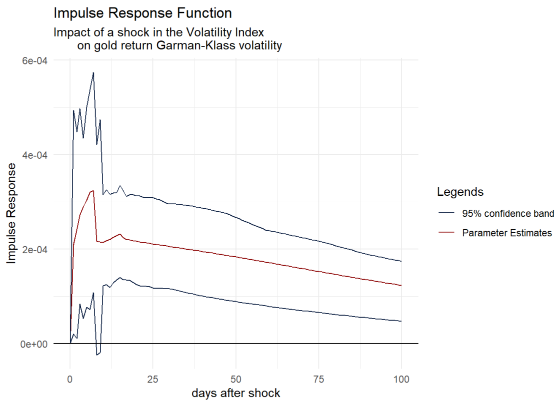


Figure 69

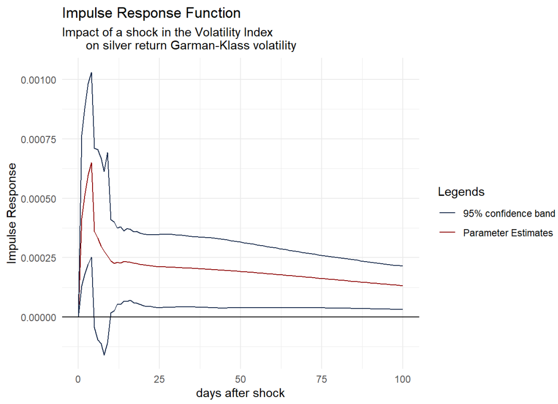


Figure 70

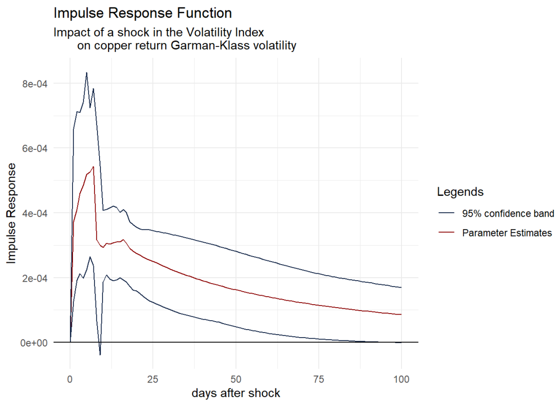


Figure 71

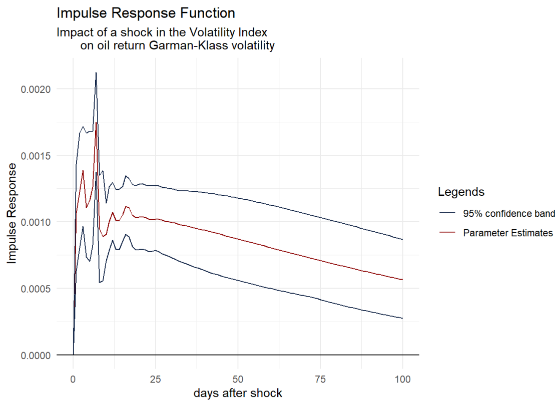


Figure 72

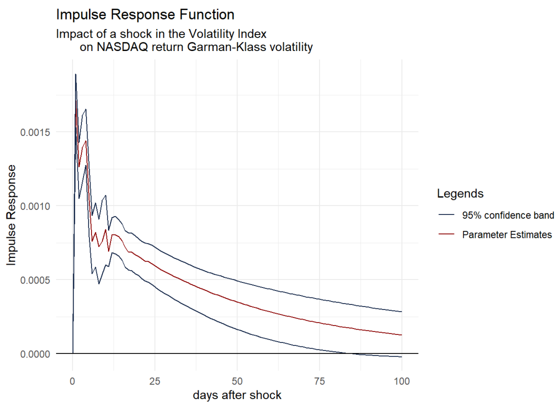


Figure 73

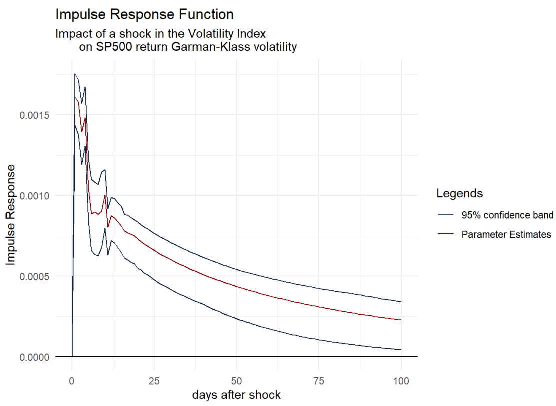


Figure 74

6.2 Credit Spreads

In this subsection, the same regressions as in the previous subsection are run with the exception of using average corporate bond yield spreads as the market uncertainty proxy.

$$\Delta\sigma_{asset,t+h} = \alpha_h + \beta_h \cdot \widetilde{CS}_t + \gamma_{1,h} \cdot \Delta EPUI_t + ... + \gamma_{m,h} \cdot \Delta EPUI_{t-m} + \delta_{1,h} \cdot \Delta GPRI_t + ... + \delta_{n,h} \cdot \Delta GRPI_{t-n} + \epsilon_{t+h}$$

, where $\Delta\sigma_{asset,t+h}$ is the differenced volatility of a prespecified asset. $\widetilde{CS}_t$ indicates the residuals of an ARIMA(1,1,1) specification of logarithmic credit spreads.

Figure 75 indicates the impact of a shock in credit spreads on the growth in gold volatility. The coefficient for h equal to zero is significant at the 1 % level. None of the other coefficients is significantly different from zero at the 5 % significance level. The peak coefficient estimate is 3.4 times that when the VIX is plugged in as a market uncertainty proxy. It is 25 times the peak coefficient estimate when GARCH volatility is used. We will compare the change in the biggest coefficient estimates to those of other assets.

The figure in the top right corner indicates the impact on the growth in silver volatility. Solely the immediate impact is significant. Even though the contemporaneous coefficient estimate for the regression with differenced silver volatility is higher than the regression with differenced gold volatility, we cannot reject the null hypothesis of the Z test. Hence, the growth of gold volatility is not less sensitive to changes in average credit spread shocks compared to the increase in silver volatility. The biggest coefficient estimate decreases by 75 % when the market uncertainty proxy is changed. Changing the way volatility is measured leads to an increase in the biggest coefficient estimate by six percent.

Figure 77 shows the impacts on differenced copper return volatility. The immediate impact is significant at the 5 % level, but solely the coefficient for h equal to three is significant at the 1 % level. However, this coefficient has a negative sign. As a result, conditional volatility sharply and significantly decreases when we change the market uncertainty proxy. The coefficient estimate for copper is once again smaller than for gold. As with all other setups considered in this paper, we cannot reject the null hypothesis that the effects on the growth of gold and copper volatility are the same. A change in the way volatility is measured resulted in a 50 % drop in the largest coefficient estimate. Altering the market uncertainty proxy causes a decrease in the peak coefficient estimate by 43.3 %.

Figure 78 indicates the impact of shock in credit spreads on differenced oil volatility. Solely the contemporaneous coefficient is significant at the 1 % significance level this time while all others are insignificant even at the 5 % level. Compared to the case where the VIX is used, the biggest coefficient estimate is now 3.4 times that from before. Another difference is that coefficient for h equal to one was significant and negative. Now, this is not the case anymore. Hence, we do not expect as sharp a drop as before. When we plug in differenced gold return volatility, the coefficient estimate for h equal to zero drops by 58.4 %. We can reject the null hypothesis that the coefficients of the contemporaneous effects are the same.

Figure 79 shows the case when differenced NASDAQ return volatility is used as the explained variable. After the significant contemporaneous impact at the 1 % level, the coefficient estimates decrease. For h equal to two, the coefficients are even negative and significant at the 5 % level, before they get insignificant again. Hence, we expect that volatility increases sharply on the day of the shock before it drops off again and then decreases gradually. The biggest coefficient estimate for the NASDAQ is 40 % higher than for the regression with differenced gold volatility as regressand. Once again, the null hypothesis of the Z test is rejected. The coefficients are the same for h equal to zero, but not for h equal to two, despite the coefficient of the NASDAQ regression being significantly different from zero. When we change the market uncertainty proxy, the contemporaneous coefficient estimate drops by 59.1 %. Altering the way volatility is measured leads to a decrease in the peak coefficient estimate by 64.3 %.

Figure 80 indicates the impacts of a shock in credit spreads on the growth of SP500 return volatility. Similar to the coefficient estimate plots for other coefficients, the contemporaneous coefficient is significant at the 1 % level. None of the other coefficients are significant even at the 5 % level. The biggest estimate is 56 % higher for the regression with differenced SP500 volatility than for a regression with differenced gold volatility. This difference is also statistically significant at the 5 % significance level according to the results of the Z test. The immediate coefficient estimate is 66.7 % lower when the conditional GARCH volatility of the asset is plugged into the regression. If credit spreads are replaced with the CBOE volatility index, the peak coefficient estimate decrease by 61.5 %.

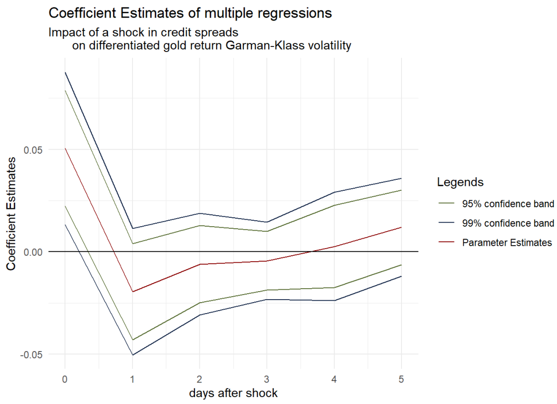
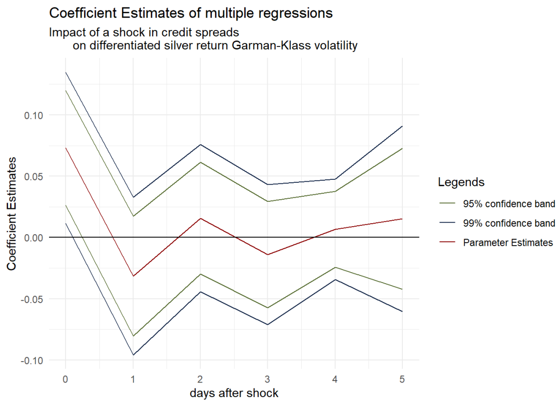


Figure 75



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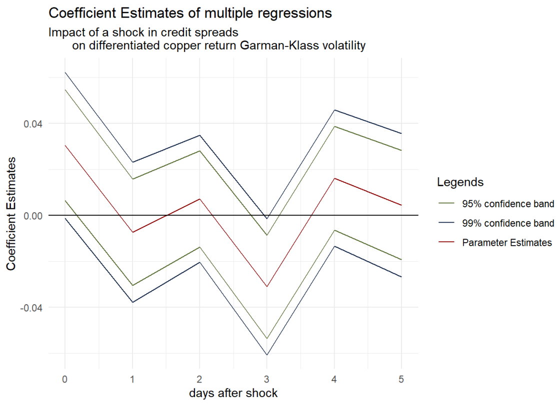
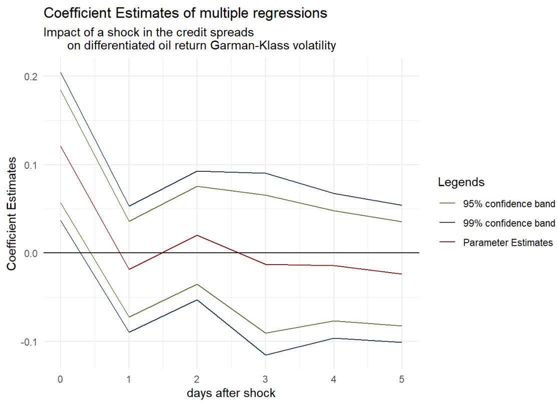


Figure 77



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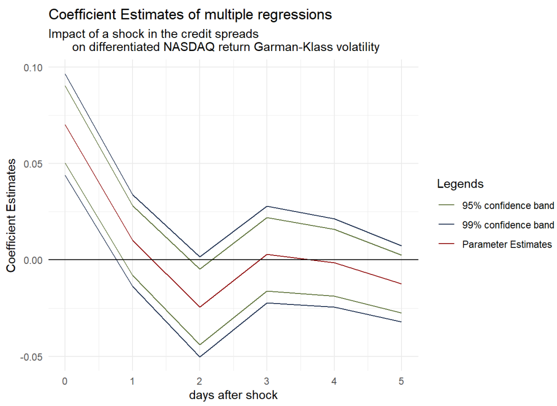

Figure 79

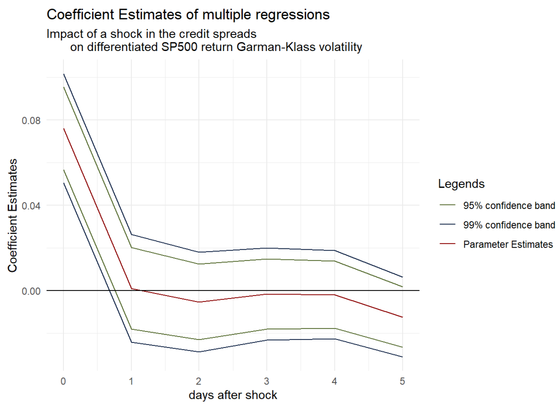

Figure 80

The graphs below show the impulse response function of a shock in the credit spreads on asset volatility. A VAR(k) model is transformed into a $VMA(\infty)$ and the choice of k is dependent on the Akaike Information Criterion. The multivariate vector autoregression is the following.

$$\begin{pmatrix} log(\sigma_{asset,t}) \\ \Delta CS_t \\ log(EPUI_t) \\ log(GPRI_t) \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \\ \phi_{30} \\ \phi_{40} \end{pmatrix} + \begin{pmatrix} \phi_{1,11} & \phi_{1,12} & \phi_{1,13} & \phi_{1,14} \\ \phi_{1,21} & \phi_{1,22} & \phi_{1,23} & \phi_{1,24} \\ \phi_{1,31} & \phi_{1,32} & \phi_{1,33} & \phi_{1,34} \\ \phi_{1,41} & \phi_{1,42} & \phi_{1,43} & \phi_{1,44} \end{pmatrix} \begin{pmatrix} log(\sigma_{asset,t-1}) \\ \Delta CS_{t-1} \\ log(EPUI_{t-1}) \\ log(GPRI_{t-1}) \end{pmatrix}$$

$$+ ... + \begin{pmatrix} \phi_{k,11} & \phi_{k,12} & \phi_{k,13} & \phi_{k,14} \\ \phi_{k,21} & \phi_{k,22} & \phi_{k,23} & \phi_{k,24} \\ \phi_{k,31} & \phi_{k,32} & \phi_{k,33} & \phi_{k,34} \\ \phi_{k,41} & \phi_{k,42} & \phi_{k,43} & \phi_{k,44} \end{pmatrix} \begin{pmatrix} log(\sigma_{asset,t-k}) \\ \Delta CS_{t-k} \\ log(EPUI_{t-k}) \\ log(GPRI_{t-k}) \end{pmatrix} + \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \end{pmatrix}$$

The impulse response functions of the six assets considered do not look smooth. It is hard to recognize the coefficient estimate for certain days because of the frequent up and down movement. Naturally, the question arises why this is the case. The downside of calculating volatilities based on intraday observations compared to conditional GARCH volatility is that the autocorrelation is lower and the time series is less persistent as we have already discussed. Naturally, this is positive when there is a regime change in volatility, as the adjustment is quicker. However, it is a disadvantage that we do not see a smooth decrease in the impulse response function. One could argue that the impulse response functions, which are calculated in the previous subsection, are not as smooth as in section 5, but certainly not as extreme as here. Hence, we have to ask ourselves what else has changed. This time, credit spreads are used as a market uncertainty proxy instead of the CBOE volatility index, which causes higher variance in the coefficient estimates of the impulse response function.

Figure 81 and 82 show the impulse response function of gold and silver volatility. The peak coefficient estimates of silver are above the ones of the gold regression. Generally, the coefficients are close to each other and the impulse response functions would intersect several times. We can reject the null hypothesis that the coefficients of the multivariate regression with gold and silver volatility are the same for h=4 at the 5 % level. For all other lags, the coefficients are not significantly distinguishable. As the coefficient estimate of the gold regression for h equal to four is lower than the coefficient estimate of the silver regression, we conclude that gold volatility is less impacted than silver volatility by a shock in credit spreads on one certain day after the shock.

Figure 83 shows relevant coefficients of a transformed vector autoregression. The biggest and smallest coefficient estimates for the first ten days after the shock in credit spreads are higher than the maximum and minimum coefficient estimates of the gold regressions in this range. We can reject the null hypothesis that the coefficients for the regressions with gold and copper volatility are the same for the second day after the initial credit spread shock. This is the only evidence found by this study that the impacts of market uncertainty shocks on gold volatility or on the growth of gold volatility are different than on copper volatility or on the growth of copper volatility.

Graph 84 indicate the impulse response function of shocks in credit spreads on oil volatility. Similar to the function for copper volatility, the immediate increase is the highest. The peak coefficient estimate is found for h equal to three. Then there is a downward trend. However, all of the first 100 coefficients are significantly different from zero at the 5 % significance level. The peak value of the impulse response function is 2.5 times the one for gold volatility. Hence, most of the coefficients of the regression with gold volatility are significantly different from those for oil.

Figure 85 and 86 look similar and one might even think that the graphs are the same at first. Resemblances are that the coefficients of both impulse response functions are significantly different from zero for all of the first 100 days after the shock or that the highest coefficient estimates are found one day after the initial credit spread shock. Moreover, both are slightly below 0.0015. We can reject the null hypothesis of the Z test for most of the coefficients for the first 100 days. Hence, we conclude that gold volatility is impacted less by shocks in credit spreads than NASDAQ and SP500 volatility. These are the same results as before. Hence, our findings are robust to the way volatility or market uncertainty is measured.

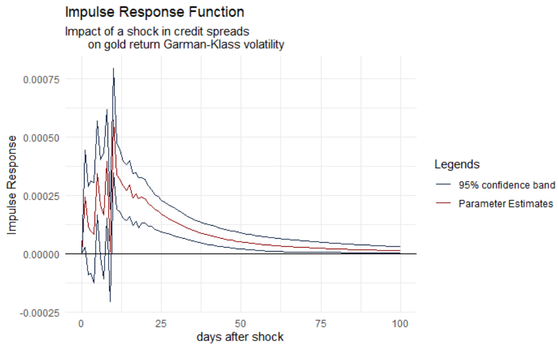

Figure 81

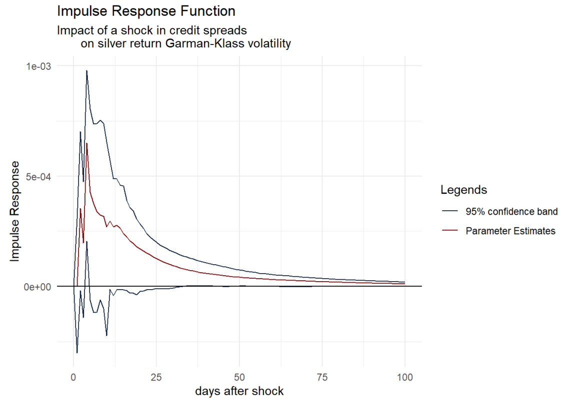

Figure 82

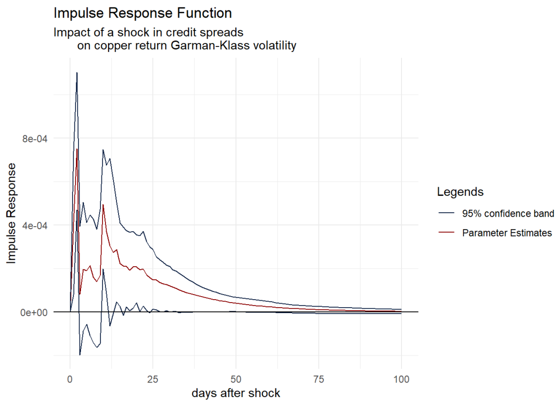

Figure 83

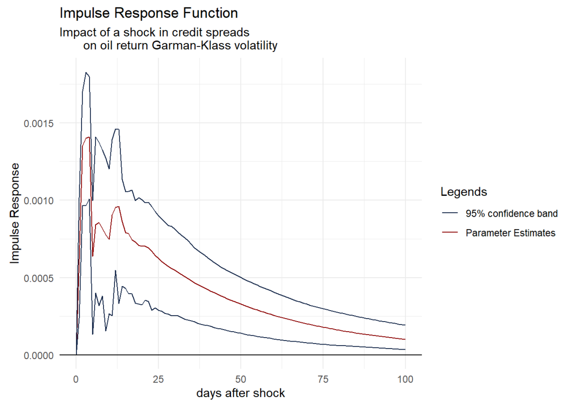

Figure 84

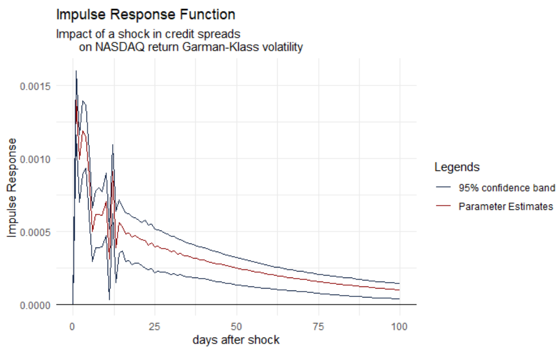

Figure 85

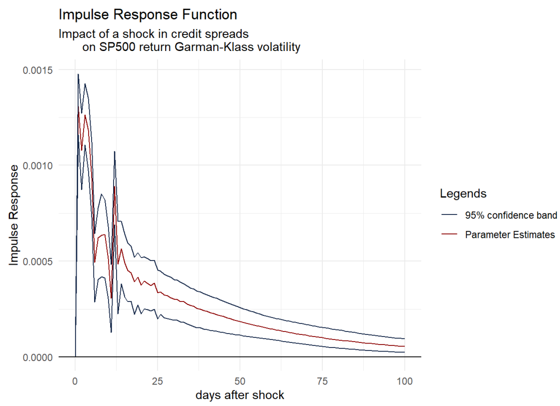

Figure 86

7 Impacts of uncertainty shock on the dynamic conditional correlation of assets with a market portfolio

This paper also aims to analyze whether uncertainty impacts the correlation of an asset with the market. A strong (weak) safe haven is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio in certain periods only, e.g. in times of falling stock markets, as defined by Baur and McDermott (2010). Hence, we run similar univariate and multivariate regressions as in the previous sections but replace conditional volatility with the dynamic conditional correlation of an asset with the market portfolio. Given that gold fulfills the role of a safe haven, the correlation of gold with the market is negatively impacted or is unaffected by shocks in market uncertainty. We run the same regression with silver, copper, oil, and the NASDAQ. The coefficients of these regressions are compared to the ones using the correlation between gold and the market to assess whether the role of gold is exceptional and uncommon in times of uncertainty.

Hence, we want to obtain the dynamic conditional correlation of each asset with the market portfolio in the first step, which is the SP500 in this example. The procedure for building an appropriate DCC-GARCH model is suggested by Tsay (2012). At first, the univariate GARCH specifications for each component series need to be defined. Chapter 4 has already discussed this problem in detail. The results are used here too. The lag order of the DCC model is decided based on the AIC. Serial and cross-correlations of the standardized residuals are calculated after the model estimation and it is checked whether the model is appropriate. Dynamic conditional correlations are obtained next and visualized below. The correlation of gold with the SP500 fluctuates between -0.6 and 0.6 with one exception in 2015. A DCC(1,1) model with a multivariate t-distribution is chosen. It is not straightforward to evaluate whether the conditional correlation is higher or lower in times of crisis solely by looking at the graph. The dynamic conditional correlation decreased sharply when the Covid pandemic broke out in early 2020. Furthermore, the correlation of gold with the market seems to be at a higher level before and after than during the Great Recession. However, the lowest conditional correlation of gold with the market occurred in late June 2016, when it dropped below -0.6. All uncertainty proxies used in this paper have a local maximum at that time. However, market uncertainty is lower than at the beginning of the Covid crisis or during the Great Recession, according to both proxies. The variance of the conditional correlation of gold is 0.033, which is higher than for most other assets considered in this paper. We can observe shifts in the dynamic conditional correlation by 0.5 within a couple of days several times. This is rarely the case for the dynamic conditional correlation of other assets. Hence, this paper regresses market uncertainty proxies on the conditional correlation of an asset and the SP500 to reveal potential dynamic causal effects.

The dynamic conditional correlation between silver and the market portfolio is positive throughout the whole time. Therefore, it is higher than the correlation of gold with the market on average. A DCC(1,1) model with a multivariate t distribution is chosen. The average correlation of silver with the market was at a lower level during than before and after the Great Recession. A drop in the dynamic correlation cannot be detected in early February 2020. Instead, there is an increase during that time. The highest conditional correlation occurred in early 2010. Hence, similarities and differences between the dynamic conditional correlation of gold and silver with the market portfolio are detected. It is not clear how the dynamic conditional correlation of silver with the market reacts in times of uncertainty by solely looking at the plot of the correlation over time.

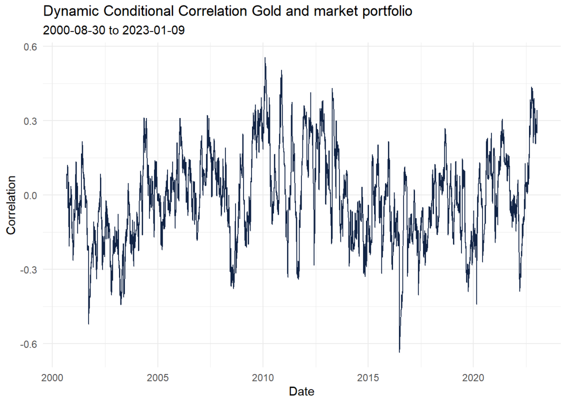

Figure 87

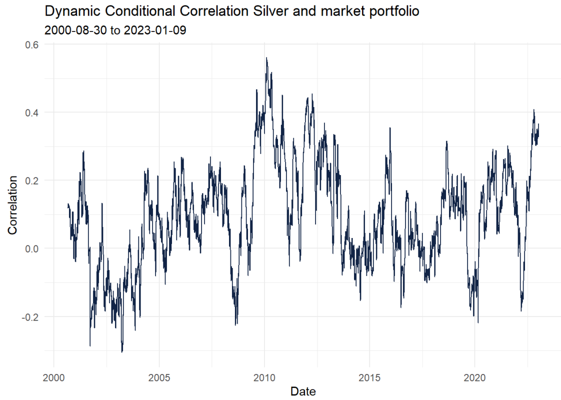

Figure 88

The correlation of copper with the market is higher than for the two precious metals on average. The unconditional correlation is -0.011 for gold and 0.095 for silver. The unconditional correlation for copper is 0.274. Once again, a DCC(1,1) specification with a multivariate t-distribution is chosen based on the suggestion of the AIC. The lowest conditional correlation is found in mid-July 2008 during the Great Recession. Several sharp increases followed afterward such that the correlation was at a high level in early 2009 compared to the average conditional correlation throughout the whole timeline. The variance of the dynamic conditional correlation of copper is lower than those of gold and silver. It is 0.0167 for copper compared with 0.0235 for silver and 0.033 for gold. It is not clear whether there is a positive or negative impact of an increase in market uncertainty on the correlation of copper with the market solely looking at the visualization of the time series.

Figure 90 shows the time series of the dynamic conditional correlation of oil with the market portfolio. A DCC(1,1) model with a multivariate t-distribution is chosen. There is a shift in the conditional correlation after the financial crisis. The mean conditional correlation was slightly above 0 from 2000 to 2008. After a drop in July 2008, it increased from -0.25 to 0.5 within a couple of days. The average conditional correlation remained approximately at that level until 2013. The dynamic conditional correlation of gold fluctuates around a constant throughout the whole timeline as we saw in figure 87. Dissimilarly, regime changes for the time series of the dynamic conditional correlation of oil are detected. The variance of the time series of the dynamic conditional correlations of oil with the market portfolio is 0.04, which is the highest of all assets considered in this paper. Hence, the correlation of oil with the market fluctuates massively. The biggest shift occurred in early 2011 when the correlation dropped from a level above 0.5 in February 2011 to -0.38 on March 2nd, 2011. However, the dynamic correlation recovered quickly and reached 0.64 in early August 2011. Financial experts attribute this development to the Arab Spring, which was a wave of anti-government protest in the Near East, as stated by Krauss and Mouawad (2011). Therefore, it is interesting to see how geopolitical uncertainty impacts the dynamic conditional correlation of oil with the SP500 when we control for financial market uncertainty and economic policy uncertainty. A similar drop in the correlation as in figure 87 during the financial crisis or when the covid crisis broke out is not detected here. On the contrary, the conditional correlation tends to increase. This intuition is confirmed by the analysis in the following sections.

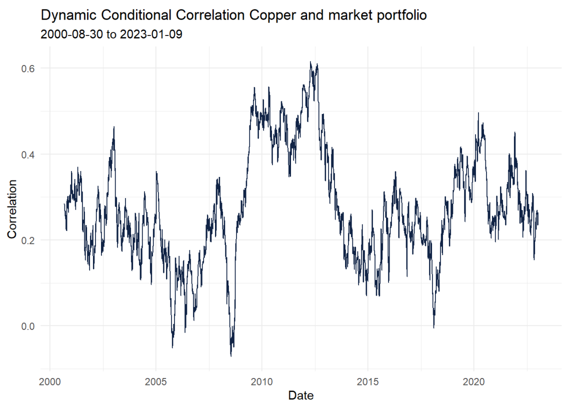

Figure 89

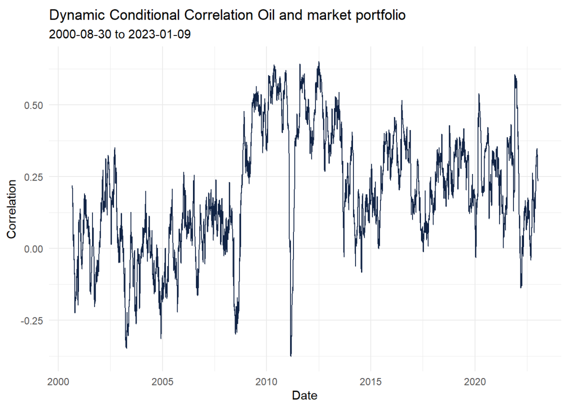

Figure 90

At last, we consider the dynamic conditional correlation of NASDAQ with the market portfolio which is chosen to be the SP500. Once again, a DCC(1,1) specification with a multivariate t-distribution is selected by the AIC. The conditional correlation of NASDAQ with the market is very high and around 0.9 on average. Furthermore, the variance of the conditional correlation is the lowest at 0.001 of all assets considered. Higher deviations from the mean conditional correlation are found for observation with a conditional correlation below the mean than for those above the mean. Hence, it is calculated that the skewness of the distribution of the dynamic conditional correlations is -1.229, which is the lowest for all assets considered. For comparison purposes, the skewness of the dynamic conditional correlation of gold with the market is 0.1213. It is hard to evaluate visually whether the correlation of NASDAQ with the market increases or decreases in times of uncertainty. One sudden shift occurred in early December 2017. Financial Analysts attribute this to a tax cut that was passed in the US Senate, which led to a tech selloff, as described in Otani (2017).

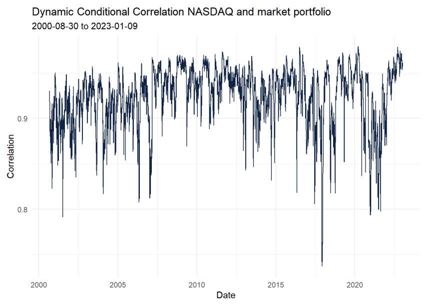

Figure 91

7.1 Volatility Index

We run the following regression in this subsection.

$$\Delta\rho_{asset,t+h} = \alpha_h + \beta_h \cdot \widetilde{VIX_t} + \gamma_{1,h} \cdot \Delta EPUI_t + ... + \gamma_{m,h} \cdot \Delta EPUI_{t-m} +$$

$$\delta_{1,h} \cdot \Delta GPRI_t + ... + \delta_{n,h} \cdot \Delta GRPI_{t-n} + \epsilon_{t+h}$$

, where $\Delta\rho_{asset,t+h}$ is the differenced correlation of an asset with a market portfolio. $\widetilde{VIX_t}$ indicates the residuals of an ARIMA(2,1,1) specification of the logarithmic CBOE Volatility Index. $\Delta EPUI$ and $\Delta GPRI$ indicate the differenced logarithmic Economic Policy Uncertainty Index and the differenced logarithmic Geopolitical Risk index. The number of lags m and n that are included in the model is decided based on the adjusted R^2. The interpretation is that a 1 % shock in the explanatory variable causes the explained variable to increase by $\frac{\beta_h}{100}$, $\frac{\gamma_h}{100}$ or $\frac{\delta_h}{100}$ in expectation, as we are running a level-log regression.

Once again, we have to think about whether all asymptotic properties of OLS are fulfilled. All variables used are stationary. Moreover, the model is linear in parameters. The dynamic conditional correlations of all assets have a high and long-lasting serial correlation. Hence, weak dependence is not fulfilled, which is why differenced conditional correlations are used in order to fulfill TS.1'. TS.2' of no perfect collinearity is also satisfied. With a similar justification as before, this regression fulfills contemporaneous exogeneity.

TS.4' and TS.5' are usually not fulfilled. Hence, heteroskedasticity or heteroskedasticity and autocorrelation consistent standard errors are used, depending on the results of several statistical tests.

Additionally, we also run the following multivariate VAR(k) regression

$$\begin{pmatrix} \rho_{asset,t} \\ log(VIX_t) \\ log(EPUI_t) \\ log(GPRI_t) \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \\ \phi_{30} \\ \phi_{40} \end{pmatrix} + \begin{pmatrix} \phi_{1,11} & \phi_{1,12} & \phi_{1,13} & \phi_{1,14} \\ \phi_{1,21} & \phi_{1,22} & \phi_{1,23} & \phi_{1,24} \\ \phi_{1,31} & \phi_{1,32} & \phi_{1,33} & \phi_{1,34} \\ \phi_{1,41} & \phi_{1,42} & \phi_{1,43} & \phi_{1,44} \end{pmatrix} \begin{pmatrix} \rho_{asset,t-1} \\ log(VIX_{t-1}) \\ log(EPUI_{t-1}) \\ log(GPRI_{t-1}) \end{pmatrix}$$

$$
+ \ldots + \begin{pmatrix} \phi_{k,11} & \phi_{k,12} & \phi_{k,13} & \phi_{k,14} \\ \phi_{k,21} & \phi_{k,22} & \phi_{k,23} & \phi_{k,24} \\ \phi_{k,31} & \phi_{k,32} & \phi_{k,33} & \phi_{k,34} \\ \phi_{k,41} & \phi_{k,42} & \phi_{k,43} & \phi_{k,44} \end{pmatrix} \begin{pmatrix} \rho_{asset,t-k} \\ log(VIX_{t-k}) \\ log(EPUI_{t-k}) \\ log(GPRI_{t-k}) \end{pmatrix} + \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \end{pmatrix}
$$

, where k is decided based on the AIC. Then the VAR(k) model is transformed into a $VMA(\infty)$ model from which the impulse response function is obtained. A 1 % exogenous increase in the VIX is expected to increase the correlation of an asset with the market by the coefficient estimate divided by 100.

7.1.1 Gold

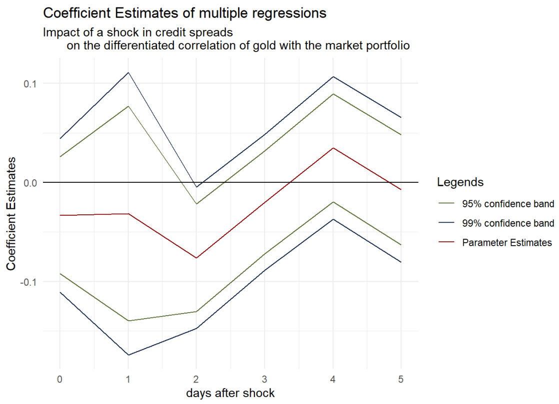

Figure 92

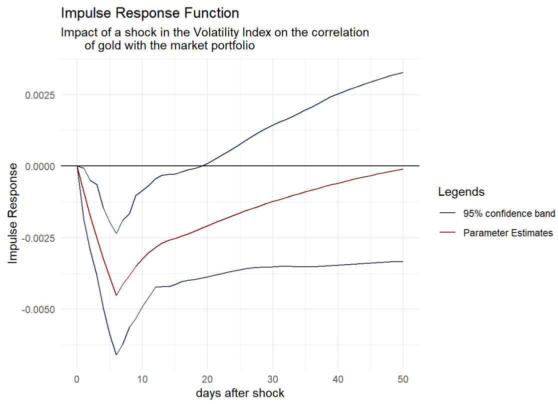

Figure 93

A 1 % shock or innovation in the volatility index is expected to increase differenced gold correlation with the market portfolio by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. The β coefficient estimates of the first three regressions are negative. Then, it is positive for h equal to four before the estimates get negative again. Although the lowest coefficient estimate is found one day after the shock, this one is not statistically significant at the 5 % significance level, as the confidence bands are wider than for h equal to three or five. We can reject the null hypothesis that β_h is zero for h equal to three and five at the 5 % significance level. With one exception, gold is the only asset or index considered in this paper for which the coefficients of this regression are significant and negative. The interpretation that the correlation of gold with the market portfolio is negative in times of high market uncertainty is incorrect. The correct understanding is that growth in the correlation of gold and the market portfolio is expected to decrease when there occurs a shock in the volatility index. Figure 92 shows that gold fulfills the property of a safe haven at the 5 % significance level, as defined by O'Connor et al. (2015). The impact on growth in the correlation of gold and the market portfolio is not significant at the 1 % level. Figure 93 displays the impulse response function of the correlation of gold with the market portfolio on an innovation in the volatility index. The coefficient estimates decrease for the first six days and the coefficients are significant from the second day after the shock. Then the coefficients increase gradually. We can not reject the null hypothesis that β_h is zero after the eleventh day. The coefficients get insignificant earlier compared to the regression with conditional gold volatility. The reason is that the serial correlation coefficients of the dynamic conditional correlation of gold are lower than the coefficients of the autocorrelation function of the conditional volatility of gold. Hence, the gradual return to zero of the coefficients in 93 is faster. $\gamma_{1,h}$ and $\delta_{1,h}$ are not significant this time. Hence, neither economic policy uncertainty nor geopolitical uncertainty have explanatory power for the growth in the correlation of gold with the market portfolio, when we control for market uncertainty and other factors.

The results of both the univariate and multivariate analysis indicate that the correlation of gold with the market is expected to decrease following a shock in the VIX when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. Hence, gold fulfills the property of being a safe haven. In order to assess whether this is a unique characteristic of gold, we compare the results to those of other assets.

7.1.2 NASDAQ

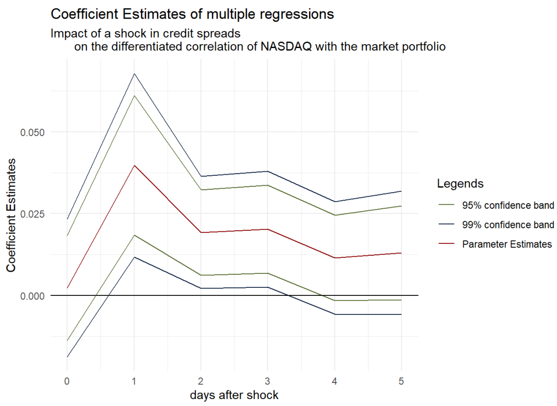

Figure 94

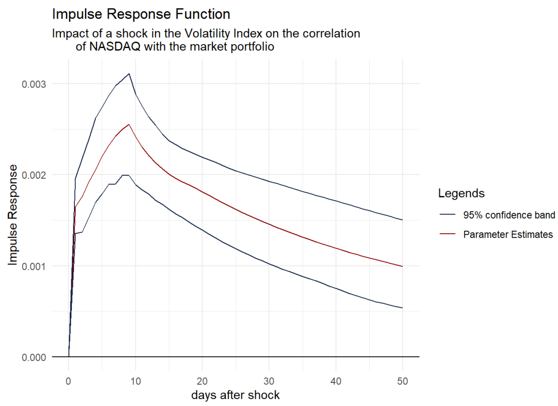

Figure 95

A 1 % shock or innovation in credit spreads is expected to increase the differenced correlation of NASDAQ with the market portfolio by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for the first, third, fourth, and fifth days after the shock at the 5 % significance level. The null hypothesis is rejected for h equal to one, three, and four at the 1 % significance level. NASDAQ returns are tied closely to those of the market in times of uncertainty, while gold returns are expected to be less correlated in such times. The unconditional correlation between gold and the market is -0.01 and the one of the NASDAQ is 0.91. The biggest absolute coefficient estimate of the univariate regression with the differenced correlation between gold and the market is slightly below the biggest absolute coefficient estimate of the univariate regression with differenced NASDAQ correlation. β_2 is not significantly different from zero, while β_1 and β_3 are significant. We have already discussed and interpreted similar results in previous subsections. The conditional correlation reacts very quickly and grows disproportionately such that no significant growth two days after the shock occurs. Figure 95 shows that the impulse response function increases sharply one day after the market uncertainty shock. Growth decreases thereafter but is positive until the peak is reached after nine days. Subsequently, the coefficient estimates decline gradually, but are still statistically significantly different from zero after 50 days. The impacts of a shock in market uncertainty are lasting much longer compared to the gold coefficients. However, the peak value of the impulse responses is bigger for gold than for the NASDAQ index in absolute terms. $\gamma_{1,h}$ and $\delta_{1,h}$ are also insignificant this time.

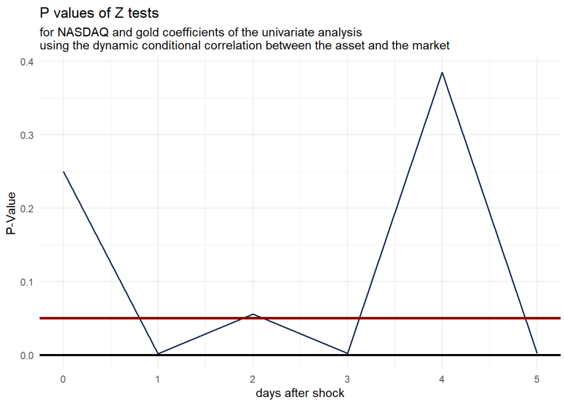

Figure 96

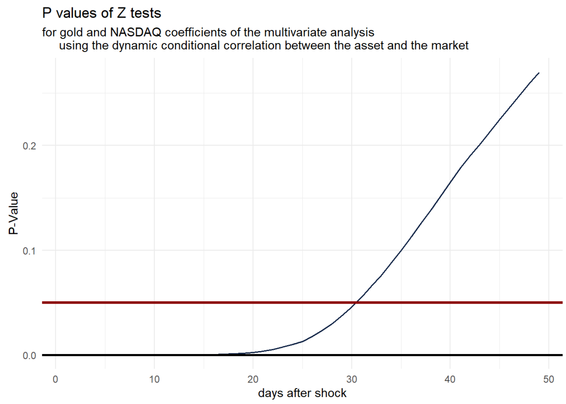

Figure 97

As coefficients of both the univariate and multivariate regression for gold are negative and significant and those of the NASDAQ are positive and significant, it is no surprise that we can reject the null hypothesis that the coefficients are the same for some h. The null hypothesis is rejected for those coefficients for which the leads of the explained variable are one, three, and five for the univariate regression. Keep in mind that the coefficient of gold for h equal to one is even insignificant.

The results of both the univariate and multivariate regressions indicate that the correlation of NASDAQ with the market is positively impacted by a shock in credit spreads when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that the coefficients are the same. The correlation of gold with the market is impacted differently by a shock in credit spreads than the correlation of NASDAQ with the market. This strengthens the claim that gold has an exceptional role as a safe haven. Certainly, the NASDAQ index does not have this property.

7.1.3 Oil

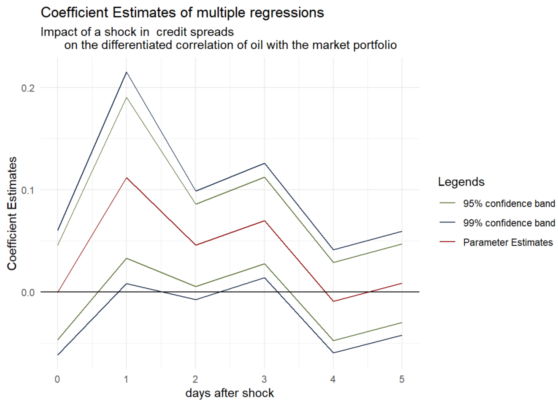

Figure 98

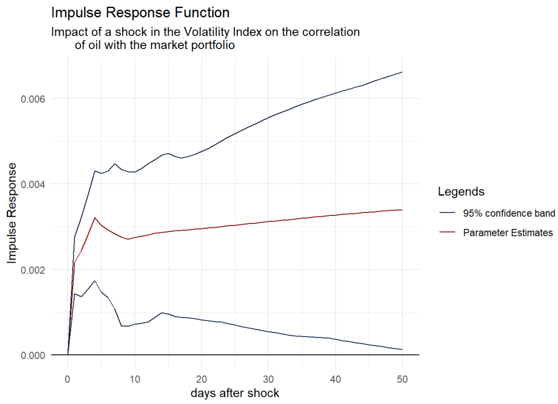

Figure 99

A 1 % shock or innovation in the volatility index is expected to increase the correlation between oil and the market portfolio by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We reject the null hypothesis that β_h is zero for h equal to one at the 5 % significance level. We have to take a close look to make sure that we cannot reject the null hypothesis even at the 1 % level, but the numbers confirm that the 99 % confidence bands include zero. Hence, the growth of the conditional correlation of oil with the market is expected to increase following a shock in the VIX. The biggest absolute coefficient estimate is 50 % higher for oil than for gold and 25 % higher than for the NASDAQ. No further significant impacts are found after the positive and significant impact for h equal to one. Figure 99 indicates the impulse response of the the conditional correlation between oil and the market portfolio on an exogenous shock in the volatility index. The increase one day after the initial shock is sharp, which is in line with the findings from figure 98. This upsurge is followed by smaller increases. Note that these coefficients of the regression with oil volatility are significantly different from zero even though the growth is not significantly different from zero. The first local maximum for h equal to four shows that the absolute functional value of the impulse response function is higher than the absolute peak value of the impulse response function for the NASDAQ, but not for gold. Hence, the correlation of oil with the market is more sensitive to a shock in the VIX than the NASDAQ but less sensitive than gold. After a short decrease between five to nine days after the shock, a further gradual increase up to 50 days after the initial shock is found. The answer for the long increase of the IRF is the high autocorrelation function coefficients of the correlation oil with the market. It shows specifically high and significant coefficients for up to 100 lags. This explains why there is no gradual decline as we have seen before. Neither $\gamma_{1,h}$ nor $\delta_{1,h}$ are significantly different from zero.

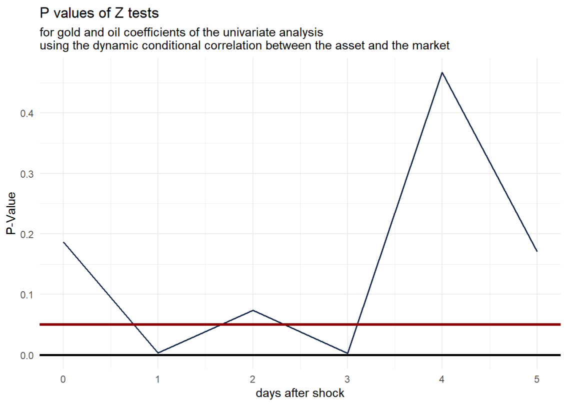

Figure 100

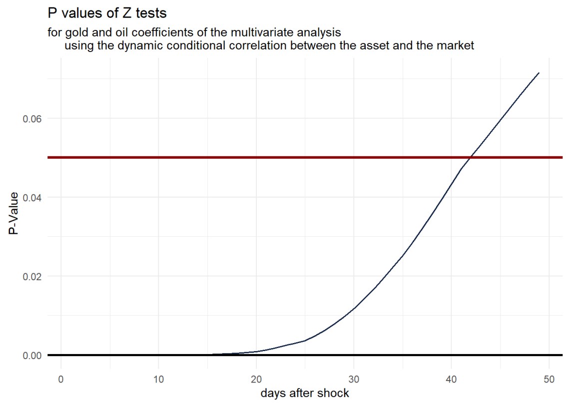

Figure 101

Graph 100 indicates that the p-values of the Z tests are below 0.05 for h equal to one and three. Hence, shocks in the volatility index impact the growth in the correlation of gold with the market and oil with the market differently. Furthermore, the p-values of the Z tests of the multivariate analysis are below 0.05 for the first 42 days after the shock.

The results of both the univariate and multivariate regressions indicate that the correlation of oil with the market is positively impacted by a shock in the VIX when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that the coefficients are the same. Oil certainly does not fulfill the characteristic of a safe haven. Furthermore, the results underline the rarity of the role of gold in times of high market uncertainty, as other natural resources like oil have different characteristics.

7.1.4 Copper

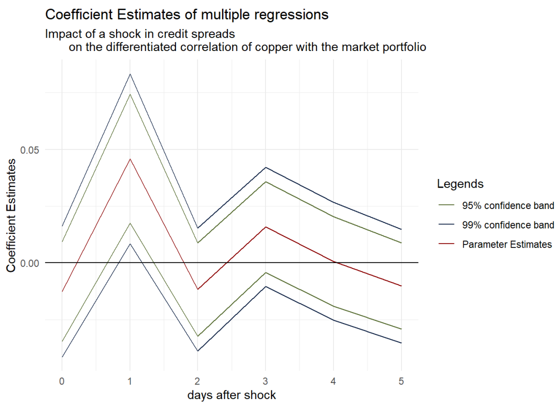

Figure 102

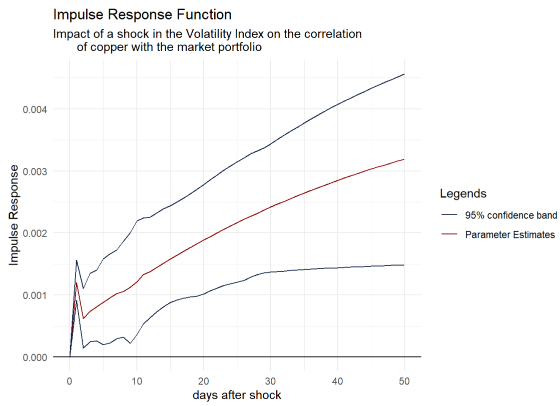

Figure 103

A 1 % shock or innovation in the volatility index is expected to increase copper correlation with the market portfolio by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h equal to 1 and 2 at the 1 % significance level. However, it is interesting that the coefficient for h equal to one is significant and positive and the coefficient for h equal to two is significant and negative. Hence, a shock in the VIX causes conditional copper correlation with the market to increase quickly but the correlation drops right afterward. We have already seen similar cases before. Later, it is checked whether we can reject the null hypothesis that the beta coefficient of the univariate regression with gold is the same as the beta coefficient of copper, as the growth of the correlation of copper with the market may be impacted significantly different than gold. Figure 102 displays that the positive significant coefficient is bigger than the negative significant coefficient, which is why we expect that the reaction of the correlation of copper with the market portfolio to a shock in the VIX is positive. Furthermore, the peak coefficient estimate of the univariate regression with differenced copper volatility is the smallest in absolute terms. Hence, the differenced correlation between copper and the SP500 is comparably unaffected by VIX shocks. Figure 103 outlines a unique impulse response function to a shock in the VIX. Changes in the growth in the impulse response function are as expected when looking at figure 102. A sudden increase is followed by a sharp drop in the function. A gradual decrease is expected as the coefficients in figure 102 are not significant for higher h. However, even though the growth itself is not statistically significant, the impulse response function gradually increases for h between 2 and 50. The highest impact is not reached even after 50 days. All of the first 50 [1,2]-elements of the coefficient matrices of the multivariate $VMA(\infty)$ specification are statistically significantly different from zero at the 5 % significance level. Similar to the impulse response function of oil and unlike the functions of gold and the NASDAQ, it takes particularly long until the peak impacts are reached. This is caused by specifically high persistency in the conditional correlation between copper and the market. The biggest impact of the impulse response function is below the ones from the IRF using oil correlation but above the ones from the impulse responses using NASDAQ correlation. The interpretation is not that copper is closer correlated to the market portfolio in times of uncertainty than the NASDAQ, as the unconditional correlation of copper with the market is 0.27 while it is 0.92 for the NASDAQ. Even though the correlation of copper with the market increases more than that of NASDAQ with the market in times of uncertainty, this does not mean that the correlation of copper with the SP500 is higher than that of NASDAQ with the market. Furthermore, the results indicate that copper does not fulfill the role of a safe haven.

Additionally, we can reject the null hypothesis that $\gamma_{1,h}$ is zero for h equal to zero at the 5 % level. Hence, copper is impacted by exogenous shocks in economic policy uncertainty even when we control for market uncertainty and other factors. Copper is the only asset considered in this paper with this characteristic. The coefficient measuring the impact of an exogenous shock in geopolitical risk is not significantly different from zero.

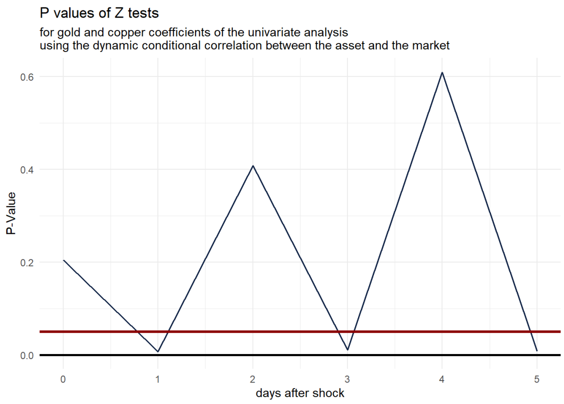

Figure 104

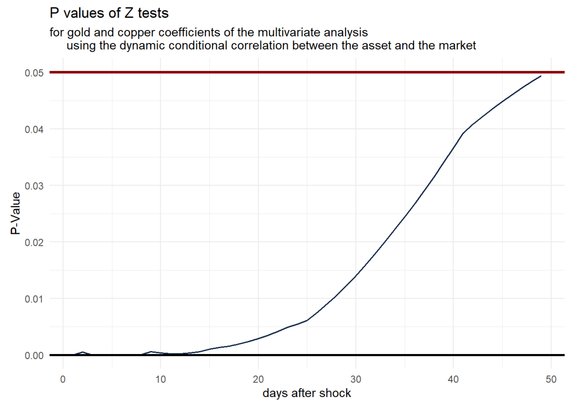

Figure 105

Figure 104 indicates that the p-values are below 0.05 for h equal to one, three, and five. Hence, we conclude that shocks in the volatility index impact the correlation of gold with the market and copper with the market differently. The coefficients are not significantly different from each other for h equal to two. Remember that the growth in the correlation of copper with the market portfolio is negatively impacted on the second day after the initial market uncertainty shock. However, we cannot state that the differenced correlation of copper is impacted significantly more negative than the differenced correlation of gold with the market at any point. These findings emphasize the distinct role of gold. Furthermore, the p values of the Z test of the multivariate regression are below 0.05 for more than 50 days.

The multivariate analysis indicates that the correlation of copper with the market is positively impacted by a shock in the VIX when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. The results of the univariate analysis point out that there are both positive and negative significant impacts on the differenced correlation of copper with the market. The conditional correlation of gold with the market is impacted differently by a shock in the VIX than the correlation of copper with the market. The negative significant coefficients are not significantly different from the impacts on the correlation of gold with the market. The reaction of the correlation of copper with the market portfolio is certainly unique compared to other assets. Figure 102 displays that the growth of conditional copper correlation with the market is positively and then negatively impacted by shocks. However, the conditional correlation is certainly expected to increase, as the significant drop after two days is followed by further non-significant growth. Copper does not satisfy the characteristics of a safe haven overall. The role of the correlation of gold with a market portfolio is still unprecedented, even compared with other metals. In the next subsubsection, we want to find out whether the role of gold is also unique compared with other precious metals.

7.1.5 Silver

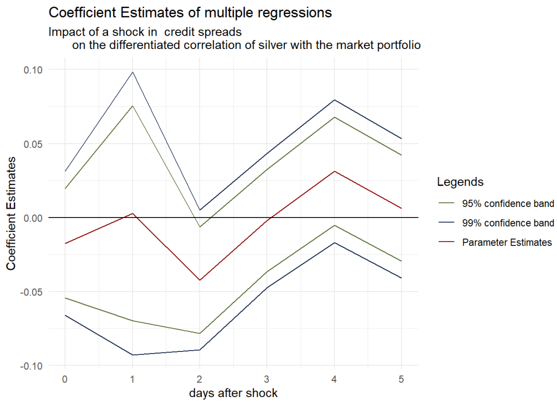

Figure 106

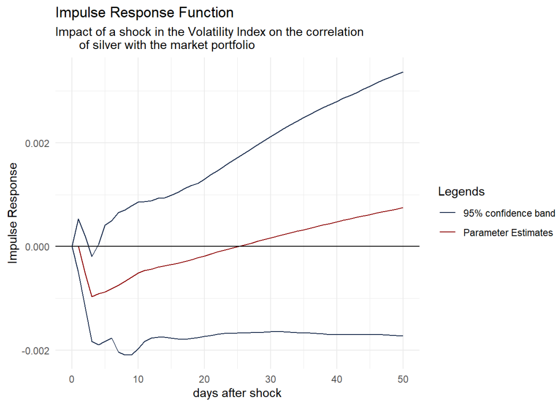

Figure 107

A 1 % shock or innovation in the volatility index is expected to increase silver correlation with the market portfolio by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We cannot reject the null hypothesis that β_h is zero for all h. Hence, the growth in the correlation of silver with the market is never statistically significant. The conditional correlation with the market is independent of VIX market uncertainty shocks for no other asset considered. The biggest coefficient estimate of the univariate regressions is smaller in absolute terms than the biggest coefficient estimate of the univariate regressions of all other assets. Figure 107 displays the impulse response function of an impact of a market uncertainty shock on the correlation of silver with the market, which is calculated using a transformed VAR(10) model. The function decreases three to four days after the initial shock. We have already seen in figure 106 that the impact on the growth of the correlation of silver with the market is negative but not significant. However, we can reject the null hypothesis that the coefficient for h equal to four of a VIX shock on the correlation of silver with the market is zero at the 5 % significance level for the impulse response function. However, the 95 % confidence bands almost include zero. A significant effect is not found for any other h. The coefficient estimates gradually approach zero after the peak impact, which is also the smallest for all impulse response functions considered. $\gamma_{1,h}$ and $\delta_{1,h}$ are not significant this time. Hence, neither economic policy uncertainty nor geopolitical uncertainty has explanatory power for the growth in the correlation of silver with a market portfolio when we control for market uncertainty and other factors.

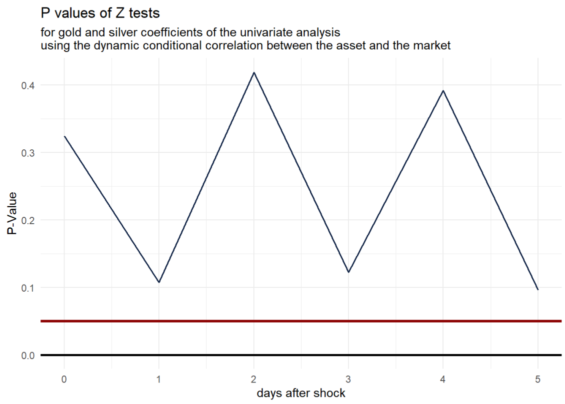

Figure 108

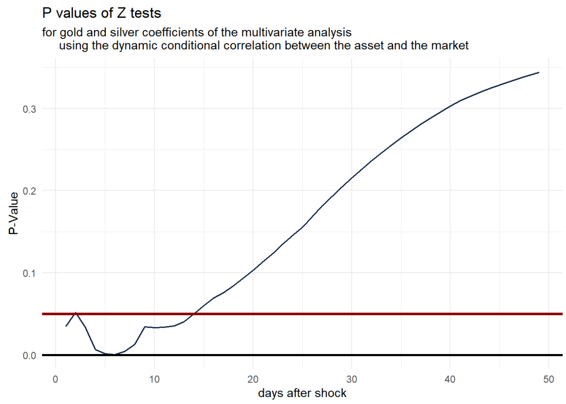

Figure 109

The p-values of the Z tests of the coefficients of the univariate regressions are never below 0.05. Hence, we cannot conclude that the growth of silver and gold correlation with the market is impacted differently. We can reject the null hypothesis that the coefficients are the same for the first 17 days after the shock for the multivariate regression.

The results of the univariate and multivariate analysis indicate that the correlation of silver with the market is not impacted by a shock in the VIX when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. Hence, the growth in the conditional correlation of no other asset is significantly impacted higher in absolute terms than gold. However, the impact on the differenced conditional correlation between gold and the market portfolio is not unique as we are unable to reject the null hypothesis that the coefficients for gold and silver are the same. We can solely reject the null hypothesis that the impacts on gold correlation with the market are different from those on the correlation of silver. That null hypothesis is dismissed for all assets considered too. Hence, a shock in the CBOE VIX market uncertainty proxy impacts the correlation of gold significantly less than silver, copper, oil, and the NASDAQ, which emphasizes the role of gold as a safe haven.

7.2 Credit Spreads

In order to evaluate the robustness of the results, we change the market uncertainty proxy once again. Average corporate bond yield spreads are used instead of the CBOE volatility index. Hence, the univariate regressions look as follows.

$$\Delta\rho_{asset,t+h} = \alpha_h + \beta_h \cdot \widetilde{CS_t} + \gamma_{1,h} \cdot \Delta EPUI_t + ... + \gamma_{m,h} \cdot \Delta EPUI_{t-m} +$$

$$\delta_{1,h} \cdot \Delta GPRI_t + ... + \delta_{n,h} \cdot \Delta GRPI_{t-n} + \epsilon_{t+h}$$

, where $\widetilde{CS_t}$ indicates the residuals of an ARIMA(1,1,1) specification of the logarithmic average credit spreads. Everything else remains the same as before.

The multivariate VAR(k) is the following.

$$\begin{pmatrix} \rho_{asset,t} \\ \Delta CS_t \\ log(EPUI_t) \\ log(GPRI_t) \end{pmatrix} = \begin{pmatrix} \phi_{10} \\ \phi_{20} \\ \phi_{30} \\ \phi_{40} \end{pmatrix} + \begin{pmatrix} \phi_{1,11} & \phi_{1,12} & \phi_{1,13} & \phi_{1,14} \\ \phi_{1,21} & \phi_{1,22} & \phi_{1,23} & \phi_{1,24} \\ \phi_{1,31} & \phi_{1,32} & \phi_{1,33} & \phi_{1,34} \\ \phi_{1,41} & \phi_{1,42} & \phi_{1,43} & \phi_{1,44} \end{pmatrix} \begin{pmatrix} \rho_{asset,t-1} \\ \Delta CS_{t-1} \\ log(EPUI_{t-1}) \\ log(GPRI_{t-1}) \end{pmatrix}$$

$$+ ... + \begin{pmatrix} \phi_{k,11} & \phi_{k,12} & \phi_{k,13} & \phi_{k,14} \\ \phi_{k,21} & \phi_{k,22} & \phi_{k,23} & \phi_{k,24} \\ \phi_{k,31} & \phi_{k,32} & \phi_{k,33} & \phi_{k,34} \\ \phi_{k,41} & \phi_{k,42} & \phi_{k,43} & \phi_{k,44} \end{pmatrix} \begin{pmatrix} \rho_{gold,t-k} \\ \Delta CS_{t-k} \\ log(EPUI_{t-k}) \\ log(GPRI_{t-k}) \end{pmatrix} + \begin{pmatrix} a_{1t} \\ a_{2t} \\ a_{3t} \\ a_{4t} \end{pmatrix}$$

, where k is decided based on the AIC. The VAR(k) model is transformed into a $VMA(\infty)$ model and the impulse response function of an increase in credit spreads on the conditional correlation between returns of an asset and the market portfolio is calculated. A one-unit increase in differenced credit spreads is expected to increase the correlation of gold with the market by the coefficient.

7.2.1 Gold

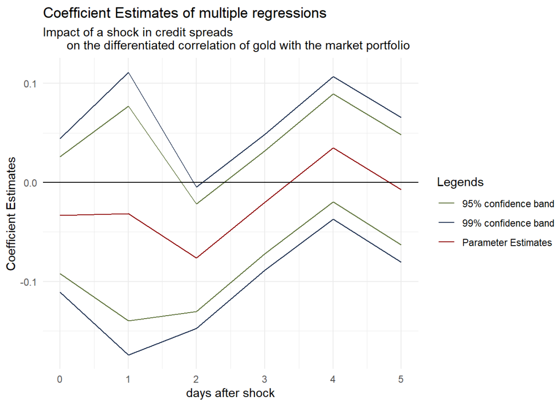

Figure 110

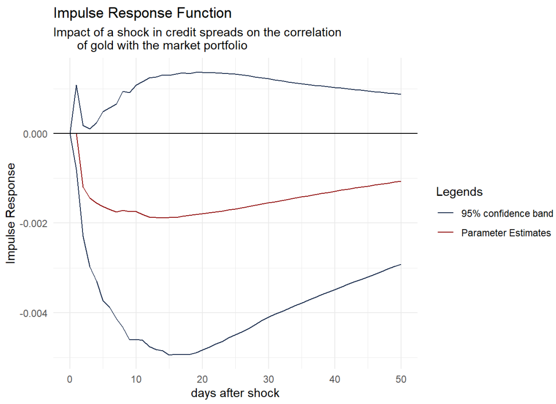

Figure 111

A 1 % shock or innovation in credit spreads is expected to increase gold correlation with the market portfolio by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h equal to two at the 1 % significance level. Gold is the only asset or index considered in this paper for which the coefficients of this regression are significant and negative at the 1 % significance level. The coefficient estimates of the univariate regressions with h equal to zero, one, three, and five are also negative, but smaller in absolute terms. We cannot reject the null that these coefficients are zero at the 5 % significance level. The peak coefficient estimates are now greater than those of the univariate regression with the VIX as the market uncertainty proxy. The ratio of the peak coefficient estimates is 3.57. Hence, a 1 % shock in credit spreads impacts the differenced correlation of gold with the market more than a 1 % shock in the volatility index. This ratio is compared with those of other assets in the following subsections to assess whether the conditional correlation of gold with the market is specifically sensitive to a certainty proxy in relation to the reaction of other assets. Figure 111 depicts the impulse response function of a shock in credit spreads on the correlation between gold and the market portfolio. A one-unit increase in differenced credit spreads is expected to decrease the correlation by 0.075. However, the coefficients are not significantly different from zero at the 5 % significance level. The biggest absolute coefficient estimate is found 14 days after the initial shock, which is roughly -0.002. This effect is 55 % less compared to the case with the VIX as the market uncertainty proxy. The functional values gradually approach zero afterward. The decrease is sharper when credit spreads are employed compared with the results from figure 93. However, the impacts on the correlation of gold with the SP500 are less such that they are solely significant when the VIX is used. Hence, whether the reaction of gold correlation with the market is significant depends on the choice of the market uncertainty proxy.

Similar to the case with the VIX as the market uncertainty proxy, neither $\gamma_{1,h}$ nor $\delta_{1,h}$ are significantly different from zero.

The results of the univariate regression indicate that the growth of the correlation of gold with the market is expected to decrease following a shock in credit spreads when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We compare the results to those of other assets in order to assess whether this result is a unique characteristic of gold. Furthermore, it is of interest whether the correlation between other assets and the market portfolio is significantly negatively impacted following shocks in corporate yield spreads, as this characteristic is not found for gold.

7.2.2 NASDAQ

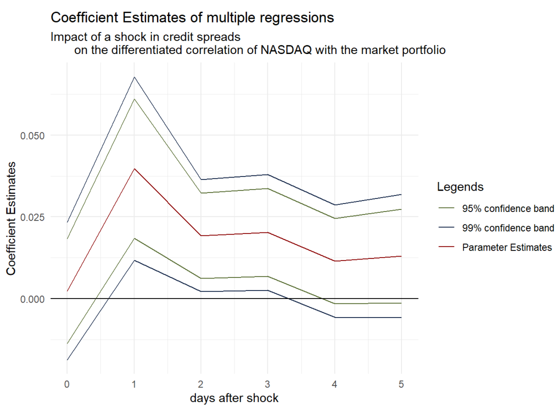

Figure 112

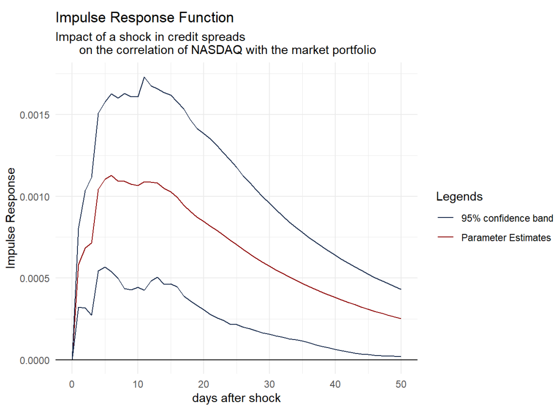

Figure 113

A 1 % shock or innovation in average credit spreads is expected to increase the differenced correlation of NASDAQ with the market portfolio by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for most of h between one and three at the 1 % significance level. The greatest coefficient estimate is roughly 0.04, which is 66 % higher than before. The ratio is lower than in the previous subsection. This is no surprise as it means that the growth in the dynamic correlation of NASDAQ with the market is more sensitive to changes in the VIX relative to changes in credit spreads, compared to the ratio for the regression using the correlation between gold and the S&P500. The biggest absolute impact on the differenced dynamic correlation of gold with the market is 75% higher than the peak impact on the differenced dynamic correlation of NASDAQ with the market. Figure 113 shows the impulse response function of a shock in yield spreads on the correlation of the NASDAQ with the market portfolio. The peak value of 0.0011 is reached after a gradual increase in the function for h between zero and six. This is approximately half of the biggest impact from the regression using the VIX as the market uncertainty proxy. A similar decrease is found for the greatest coefficient estimates when the correlation of gold with the market portfolio is used as an explained variable. Figure 113 shows that the coefficient estimates decrease gradually after the peak is reached. Moreover, we can reject the null hypothesis that the coefficients are zero at the 5 % significance level for every h between 0 and 50.

Similar to the case with VIX as the market uncertainty proxy, neither $\gamma_{1,h}$ nor $\delta_{1,h}$ are significantly different from zero.

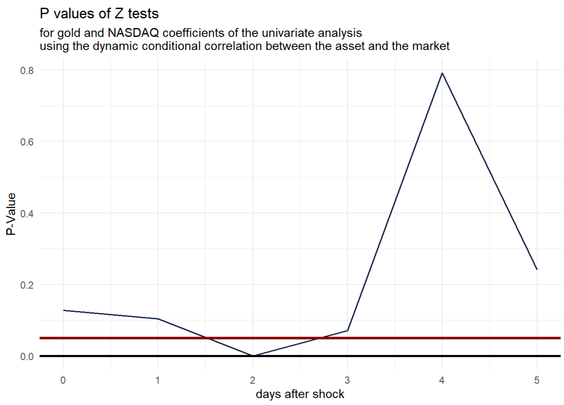

Figure 114

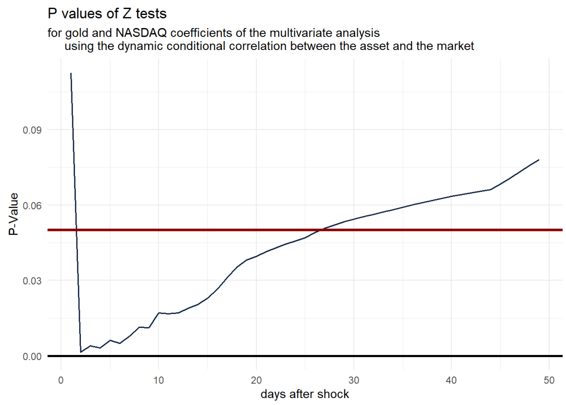

Figure 115

The graph indicates that the p-values of the Z tests are below 0.05 for h equal to two. Hence, we conclude that shocks in credit spreads impact the differenced correlation of gold with the market and NASDAQ with the market differently. These results are anticipated by looking at the confidence bands in figure 110 and 112. The other graph indicates that the p-values are below 0.05 for h between 2 and 49. As a result, shocks in credit spreads impact the correlation of gold with the market and NASDAQ with the market differently. This strengthens the distinct role of gold as a safe haven.

The results of both the univariate and multivariate regressions indicate that the correlation of NASDAQ with the market is positively impacted by a shock in credit spreads when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We reject the null hypothesis that the coefficients are the same. These results strengthen the uniqueness of the role of gold in times of financial turmoil since the main takeaways coincide when the VIX is used as the market uncertainty proxy.

7.2.3 Oil

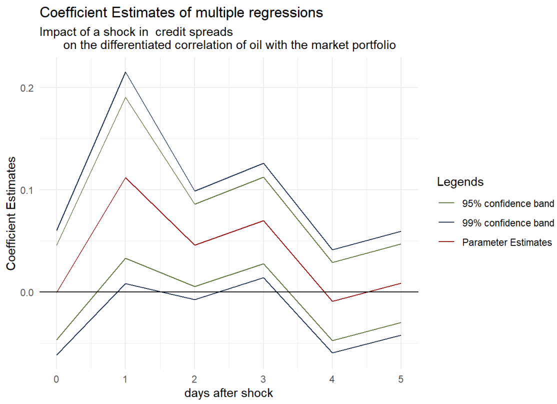

Figure 116

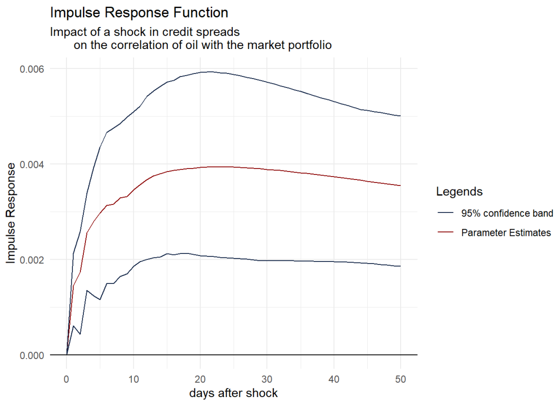

Figure 117

A 1 % shock or innovation in credit spreads is expected to increase oil correlation with the market portfolio by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h equal to one and three at the 1 % significance level. We can reject the null hypothesis for h equal to two at the 5 % significance level. The biggest coefficient estimate is approximately 0.12, which is four times the peak estimate when the CBOE VIX is used as the market uncertainty proxy. The ratio is close to the one we have found for gold, which further emphasizes that the NASDAQ is particularly sensitive to changes in the VIX. The growth in the correlation of oil with the market seems to be more sensitive to changes in credit spreads relative to the increases in the VIX, compared with other assets. The greatest coefficient estimate is above the peak coefficient estimates of gold and NASDAQ. Figure 117 depicts the impulse response function of a shock in credit spreads on the correlation of the oil with the market portfolio. The coefficient estimates are up to 0.004. The biggest estimate is greater than the one from the regression using the VIX as the market uncertainty proxy. We see decreases in the peak coefficient estimates for all other assets when the uncertainty proxy is changed to credit spreads. The impulse response function increases until h is equal to 23. The growth in the coefficients is particularly high, as figure 116 outlines. The decay is comparably slow after the peak is reached, which is attributed to the high autocorrelation of the correlation of oil with the market. This causes high persistence. We can reject the null hypothesis that the coefficients are significantly different from zero for all h at the 5 % level. There is a gradual increase in the function for h between zero and six until the peak value is reached. The greatest coefficient estimate is four times the peak estimate using the NASDAQ and twice the peak estimate in absolute terms using the correlation between gold and the S&P 500. These results highlight the sensitivity of the correlation of oil with the market to changes in credit spreads, as the difference decreases with the VIX as the market uncertainty proxy.

Similar to the case with the VIX as the market uncertainty proxy, neither $\gamma_{1,h}$ nor $\delta_{1,h}$ are significantly different from zero.

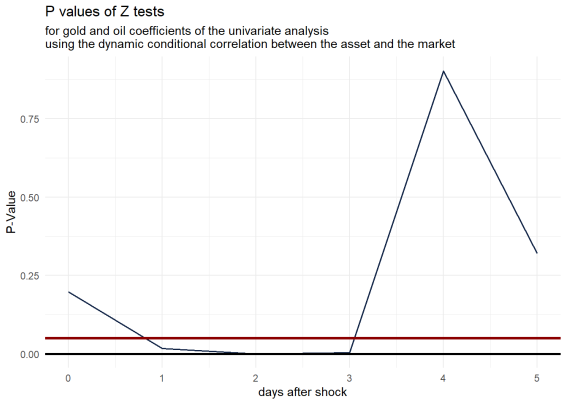

Figure 118

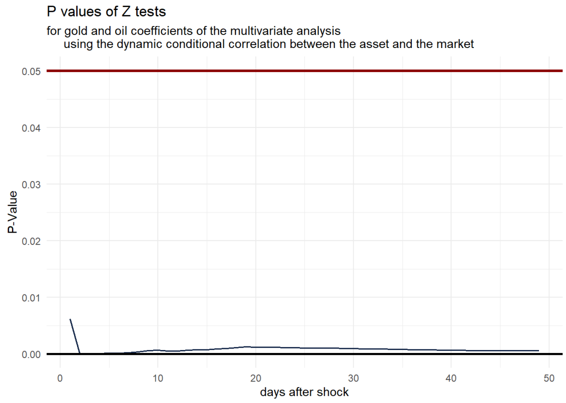

Figure 119

Figure 118 indicates that the p-values of the Z test are below 0.05 for h from one to three. Hence, shocks in average corporate bond yield spreads impact the growth in the correlation of gold with the market and oil with the market differently. The p-values of the Z test of the multivariate analysis are below 0.05 for all h. As a result, innovations in credit spreads impact the correlation of gold with the market and oil with the market differently. These results are expected when we look at the confidence bands from the coefficients of the previous regressions.

The results of both the univariate and multivariate regressions indicate that the correlation of oil with the market is positively impacted by a shock in credit spreads when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that the coefficients are the same. Hence, the results emphasize the unique role of gold as a safe haven compared to other natural resources.

7.2.4 Copper

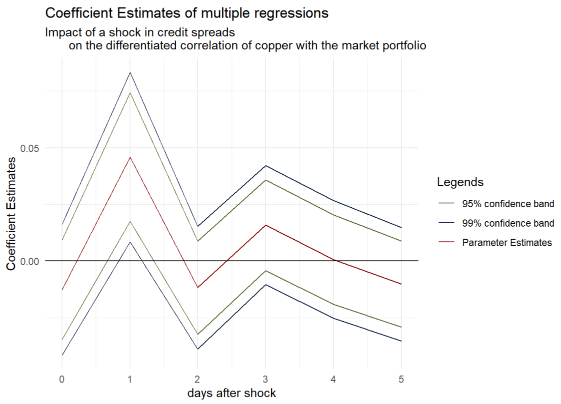

Figure 120

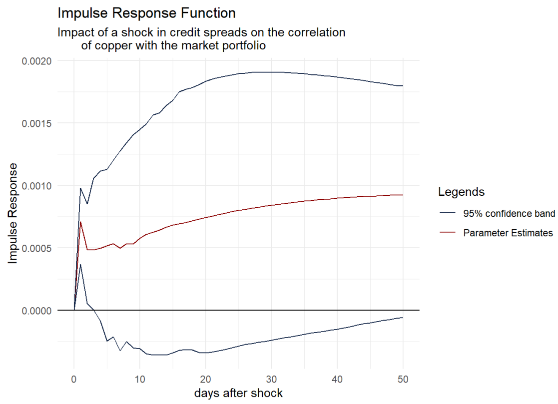

Figure 121

A 1 % shock or innovation in credit spreads is expected to increase the differenced correlation of copper with the market portfolio by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that β_h is zero for h=1. The coefficient estimate for h equal to one is 0.045, which is greater than the absolute peak coefficient estimate of the univariate regression with the NASDAQ, but smaller than the absolute peak coefficient estimate of the univariate regression with oil and gold. The ratio of the biggest impact of the univariate regression using credit spreads to the estimates using the CBOE VIX is 2.57, which is among the highest values that are found in the previous subsections. Hence, copper returns are not particularly sensitive to the selection of a specific proxy, compared to the reaction of the other assets. The shape of figure 102 indicated that β_2 is negative and significant. The coefficient estimates are still negative when credit spreads are used as the market uncertainty proxy but not significantly different from zero at the 5 % significance level. Figure 121 displays the impulse response function of a shock in average bond yield spreads on the correlation of copper with the market portfolio. The immediate increase in the correlation is followed by a decrease. The coefficient estimates grow subsequently for more than fifty days after the shock. This result is attributed to the high coefficients of the ACF of the conditional correlation of copper with the market. The shape of the impulse response function is similar to the one in figure 103. One difference is that the increase following the decrease two days after the initial shock is more gradual. However, the coefficients are only significant for equal to two or three at the 5 % significance level, while all of the first 50 coefficients are significant when the VIX is used as the market uncertainty proxy. Hence, the main takeaways depend on the choice of the market uncertainty proxy. Furthermore, the peak coefficient estimate decreased by 66 % when the market uncertainty proxy is changed. This is a sharper decrease than we have witnessed for gold. Furthermore, the peak values of the impulse response function are closer to zero than the greatest coefficient estimates of all other assets consider so far.

Similar to the case with the VIX as the market uncertainty proxy, neither $\gamma_{1,h}$ nor $\delta_{1,h}$ are significantly different from zero.

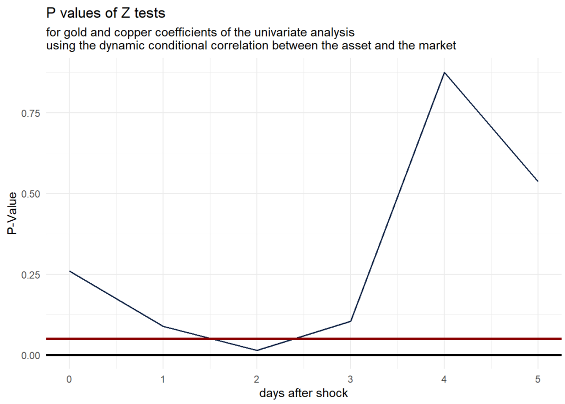

Figure 122

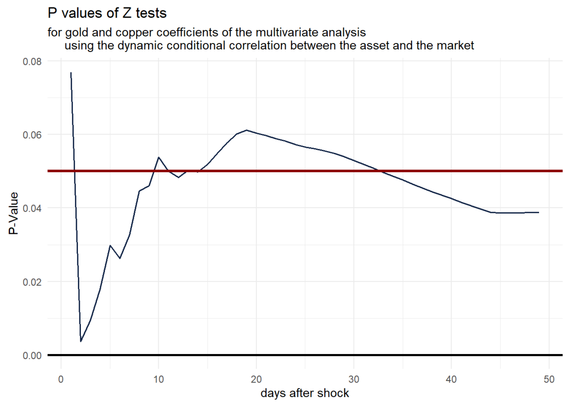

Figure 123

Graph 122 indicates that the p-values of the Z tests are below 0.05 for h equal to two. Hence, we conclude that shocks in credit spreads impact the growth in the correlation of gold with the market and copper with the market differently. The p-values of the Z test for the multivariate analysis are below 0.05 for h bigger than two with one exception.

The results of both the univariate and multivariate regressions indicate that the correlation of copper with the market is positively impacted by a shock in credit spreads when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We can reject the null hypothesis that the coefficients are the same. Because of the long time it takes until the biggest impact of a shock in credit spreads on the correlation of copper with the market is reached, the impulse response function looks unique. Note that the main results changed when we switched the market uncertainty proxy. No significant negative impacts on the growth of copper correlation are found. Furthermore, the coefficients of the impulse response function are either significant for three days or more than 50 days depending on the selection of the uncertainty proxy.

7.2.5 Silver

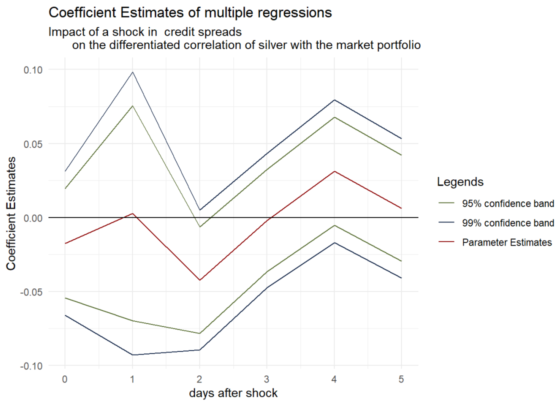

Figure 124

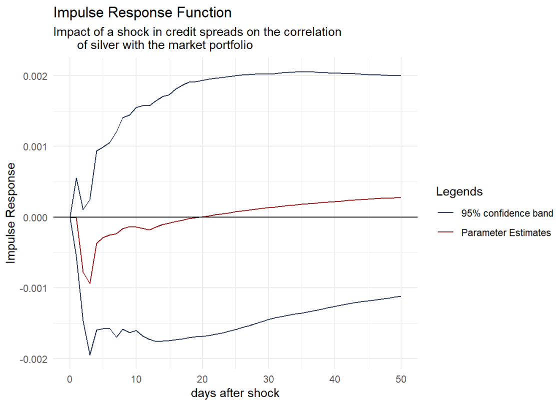

Figure 125

A 1 % shock or innovation in credit spreads is expected to increase silver correlation with the market portfolio by the value of the parameter estimate divided by 100 when we control for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. We reject the null hypothesis that β_h is zero for h equal to two at the 5 % significance level. We cannot reject the null hypothesis for any coefficient at the 1 % significance level. The biggest negative impact is also found for h equal to two when the VIX is used as the market uncertainty proxy. However, the coefficient from the previous section is not significant at the 5 % significant level. The ratio of those two coefficient estimates is 5.3. This is the highest so far. Figure 125 shows the impulse response function of a shock in credit spreads on the correlation of silver with the market portfolio. The function decreases quickly and the peak value peak is reached three days after the shock. The coefficient estimates gradually return to zero subsequently. However, we can reject the null hypothesis that the coefficients are different from zero for no h. When the VIX is used as a market uncertainty proxy, we reject the null hypothesis solely for h equal to three. The peak values of the impulse response function are almost independent of the choice of the market uncertainty proxy. For all other assets, we see a decrease, which further highlights the specific sensitivity of silver to changes in credit spreads. The absolute peak value is twice as high compared with gold. However, we cannot state that a shock in credit spreads significantly decreases the correlation of the asset with the market for both assets.

Similar to the case with the VIX as the market uncertainty proxy, neither $\gamma_{1,h}$ nor $\delta_{1,h}$ is significantly different from zero.

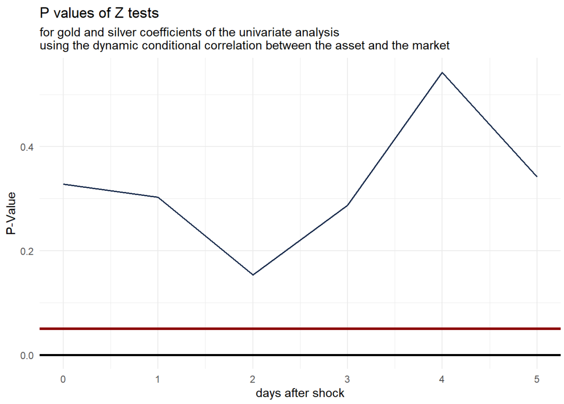

Figure 126

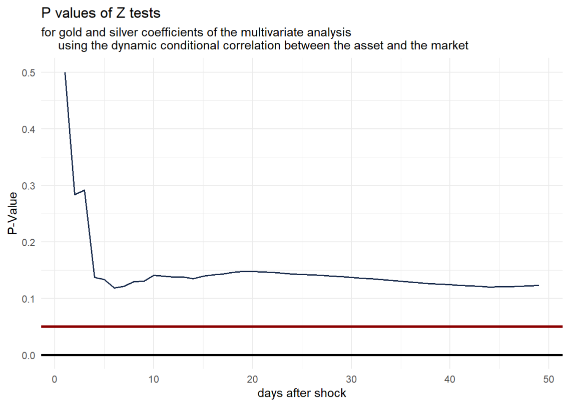

Figure 127

Figure 126 indicates that the p-values of the Z test are never below 0.05. Hence, we cannot conclude that shocks in credit spreads impact the growth in the correlation of gold with the market and silver with the market differently. The same is true for the coefficients of the multivariate regression.

The result from the univariate analysis indicates that the correlation of silver with the market is impacted by a shock in credit spreads at the 5 % significance level when controlling for the Economic Policy Uncertainty Index and the Geopolitical Risk Index. These results are not found for the multivariate regression, as we cannot reject the null hypothesis that the coefficients are the same. Hence, the reaction of the correlation of gold with the market portfolio in times of high market uncertainty is not unique. However, we cannot state that silver is an asset whose correlation with the market drops significantly more than gold.

8 Calculation of Minimum Variance Portfolio

So far, the findings are that the volatility of gold increases less than the volatility of the SP500, the NASDAQ, or oil. The case is not clear for silver and copper as the results depend on the way volatility is measured or on the selection of the market uncertainty proxy. It is seen that the coefficient estimates of gold are smaller than those of silver and copper. However, the null hypothesis that the coefficients are the same is sometimes rejected and sometimes we fail to reject it. Moreover, gold is one of the only asset whose correlation with the market is negatively impacted by an increase in market uncertainty. The correlation of other assets with the market is unaffected or positively impacted by such shocks. Naturally, the question arises what the social benefits of these findings are. Hence, the minimum variance portfolio consisting of gold and another asset is calculated. The formula for the variance of a portfolio consisting of gold and another asset is

$$\sigma^2_{p,h} = w_h^2 \cdot \sigma^2_{gold,h} + (1 - w_h)^2 \cdot \sigma^2_{asset,h} + 2 \cdot w_h \cdot (1 - w_h) \cdot \rho_{gold,asset;h} \cdot \sigma_{gold,h} \cdot \sigma_{asset,h}$$

This formula is provided by Gaunersdorfer (2021). We write a function that minimizes this function for every h, which is found in the appendix. The way the function is constructed forces w to be between zero and one. Hence, short-selling is not possible. Next, the volatility index is plotted alongside a two-sided moving average of the weights. Hence, we can see whether the minimum variance portfolio has a greater share of gold or the other asset in times of higher market uncertainty. Note that it is decided to use a two-sided moving average of the gold weights as we have many quick up and down movements, which make it impossible to recognize any pattern. A plot of these unadjusted weights is found in the appendix. Based on our results, we expect that the weights of gold in a minimum variance portfolio increase in times of high market uncertainty.

8.1 SP500

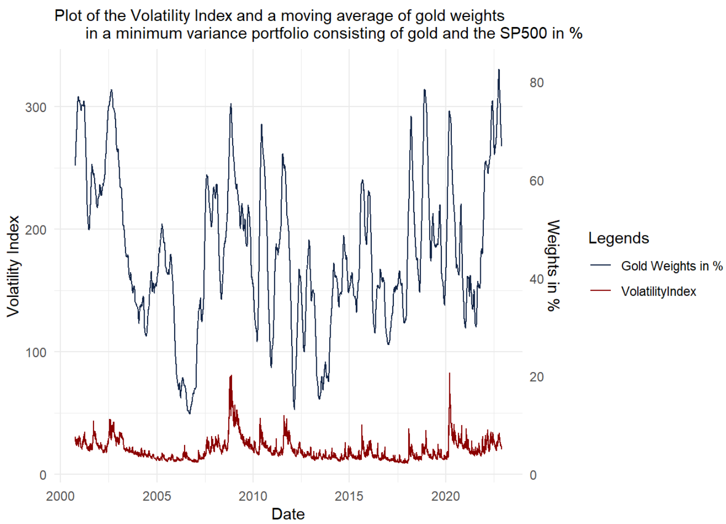

Figure 128

This figure depicts the weights of gold in a minimum variance portfolio consisting of gold and the SP500 and the CBOE volatility index over time. The share of gold in a minimum variance portfolio is expected to increase in times of higher uncertainty. For example, the weight of gold moved in the same direction as the CBOE volatility index when the Great Recession began in 2007. Similar co-movements are found repeatedly. When there is an increase in the "fear index" the weight of gold increases too. This was also the case when the covid pandemic broke out in early 2020 when the volatility index reached its highest point. However, recent developments are hardly explained by market uncertainty. Even though the mean volatility index since 2020 is above the mean volatility index of the whole timeline, the sharp increase in the weight of gold needs to be explained by other variables. The geopolitical risk index might have explanatory power as the war between Russia and Ukraine began in February 2022.

8.2 NASDAQ

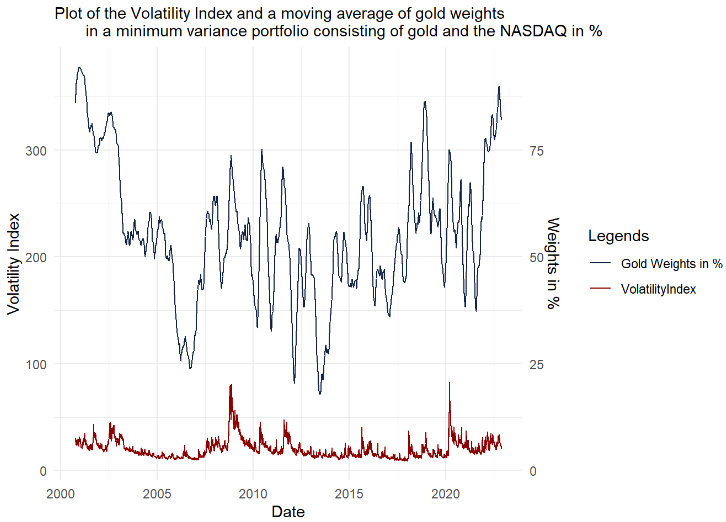

Figure 129

Figure 129 shows the weights of a minimum variance portfolio consisting of gold and the NASDAQ over time. We can also detect a co-movement. Hence, an increase in the VIX is typically accompanied by an increase in the weight of gold. The minimum variance portfolio consisted almost solely of gold in 2000. We have to remind ourselves that the Dotcom bubble burst in March 2000. Keeping almost solely gold was the best strategy in terms of minimizing portfolio variance during that time. The weight of gold tended to increase after the Great Recession or the Covid pandemic had begun. Similar to before, the current share of gold in a minimum variance portfolio can hardly be explained by market uncertainty.

9 Conclusion and Outlook

The motivation of this paper is to determine whether changes in exogenous shocks in market uncertainty significantly impact gold volatility and its correlation with the market. The results are that gold volatility is expected to rise after such an innovation. These findings are robust to the proxy chosen for market uncertainty or the way volatility is measured. Furthermore, there is either a negative impact or no significant impact of a shock in market uncertainty on the correlation between gold and the market portfolio depending on the uncertainty proxy that is chosen and whether the correlation or growth in correlation is analyzed. Furthermore, shocks in market uncertainty affect the volatility of no other asset considered in this paper significantly less than that of gold. In addition, solely the conditional correlation between the market and the precious metals analyzed in this paper is unaffected or even significantly negatively impacted. It is demonstrated that these effects have a significantly more negative impact on gold than on silver. Hence, shocks in market uncertainty affect the conditional correlation between gold and the market significantly less than that of the other assets considered. Gold has unique characteristics in times of high market uncertainty.

To reconnect these findings to the questions raised in the introduction, it is no surprise that the demand for gold as an investment asset increased when the Covid pandemic broke out in early 2020. Risk-averse institutional and private investors turn to gold because of its unsurpassed characteristics in times of uncertainty. The weight of gold in a minimum variance portfolio is expected to increase during this time. The findings of this paper help to understand why gold prices and the S&P index value moved in opposite directions after the terrorist attacks of 9/11. The conditional correlation of gold and the S&P 500, which is close to zero on average, is expected to decrease following this shock.

The findings of this paper raise further questions. The weights of gold in a minimum variance portfolio cannot be explained by movements in the VIX in recent years. Furthermore, structural changes in the coefficients measuring the impacts on gold volatility and the correlation of gold with the market are found. Hence, it can be further analyzed whether gold still fulfills the unique characteristics described in this paper when solely using data since the end of the Great Recession, the beginning of the Covid pandemic, or the Russian invasion of Ukraine.

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Appendix

A detailed appendix can be found online (https://shorturl.at/gBDXZ).