# Precious metals, Oil and the Exchange rate: Contemporaneous Spillover Effects

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**Abstract:**

We investigate the concurrent interrelationship among gold, silver, platinum, palladium, crude oil and the US dollar exchange rate for the period January 1, 1999 to December 31, 2013. We employ both the conventional reduced form VAR methodology based on lead/lag dynamics and the Structural VAR (Rigobon, 2003) based on contemporaneous relationship among precious metals, crude oil and the US dollar. We obtain stark differences in our results based on the two methodologies. We contend that by not taking into consideration the contemporaneous interrelationships among assets, traditional VAR analysis leads to inaccurate outcomes and inevitably to inaccurate interpretation of causal relationships among variables.

Key Words: Structural VAR, Precious metal prices, Oil prices, Impulse-response.

JEL CODES: O13; Q14; Q30; Q43

## 1. Introduction

We investigate the contemporaneous spillover among precious metals, crude oil as well as the US dollar exchange rate. The dynamic relations among these assets have become almost instantaneous over time, and as such modelling spill-over effects using lead-lag dynamics may not reveal the true relations among these assets. In this paper, we demonstrate how these contemporaneous relations can be modelled in a structural VAR, and empirically show that ignoring these contemporaneous relations can lead to very different outcomes with regards to the dynamic relations among the assets we investigate.

The interrelationships among precious metals, crude oil and the FX rate are intriguing and complex. For example, crude oil, its price being denominated in the US dollar, has been employed as a means for both the production and transportation of commodities including precious metals. At the same time, changes in the price of crude oil affect the overall performance of national economies with possible consequences for inflation, interest and exchange rates. For example, Lizardo and Mollick (2010) find that oil prices significantly explain fluctuations in the value of US dollar against major currencies. Moreover, changes in precious metal prices, in particular gold (which is widely recognized as a safe haven investment), have direct impact on the level of national output and consumer/producer prices as they are used for productive purposes, wealth accumulation and inflation hedging.

Of note is the role of inflation in the linkage between precious metals and crude oil markets. Macroeconomic theories, based on cost-push effects, contend that higher oil prices put upward pressure on the overall national price level. Hooker (2002) and Hunt (2006) provide empirical evidence for this relationship. Moreover, inflationary expectations may lead investors to amass precious metals, either for hedging against the erosion in their wealth (Jaffe, 1989) or for speculative purposes.

Interestingly, in recent years, due to the phenomenon known as financialization of commodities, more and more commodities are being considered for their diversification attributes. Geman and Kharoubi (2008), for example, show that the inclusion of crude oil futures in a portfolio of stocks reduces the overall riskiness of such a portfolio. Conover et al. (2009) present strong evidence on the benefits of including gold to an equity portfolio. They report that increasing the weight of gold to 25% of total portfolio holding substantially improves the overall performance. Baur and McDermott (2010) investigate the role of gold in the global financial system, for the period 1979 to 2009, and argue that gold has a stabilizing impact on the functioning of financial markets by reducing losses in the face of extreme negative market shocks. They report that gold acted as a resilient haven for investors in many European and the US markets during the recent global financial crisis.

As the majority of commodities in the international markets are priced in the US dollar, there are causal effects of the US dollar exchange rate on these commodities' prices. A decline in the value of the dollar, for example, must be offset by an increase in the dollar price of tradable commodities or a decline in their foreign currency prices to ensure the law of one price holds for such commodities. Additionally, a decline in the value of the dollar could raise the demand for commodities by foreign consumers, while reducing the returns of producing commodity countries and possibly their production (Hamilton, 2008). Additionally, with regard to the relationship between gold and the US dollar exchange rate, Capie et al. (2005), using weekly data for a period of 30 years, report that gold has served as a hedge against a drop in the foreign exchange value of the dollar.

The above arguments clearly demonstrate that many alternative channels exist through which precious metals, crude oil and the exchange rate can influence each other directly and indirectly, and that these need to be considered concurrently when studying the dynamic interactions among these assets. Although various studies examine gold and crude oil separately, a number of them examine the two together, taking into consideration the potential for interaction between the two commodity markets. Narayan et al. (2010) investigate the long-run relationship between prices of gold and crude oil futures, finding evidence of cointegration. The authors conclude that investors should use gold as a hedge against inflation, and crude oil can be used to predict gold prices and vice versa. Sari et al. (2010) investigate the spot prices of gold and crude oil using the Autoregressive Distributed Lag (ADL) approach and report strong feedback in the short run but a weak relationship over the longer horizons. Other studies often focus on a particular pair of precious metals, such as the interactions between gold and silver (Lucey and Tully, 2006), or the pair of platinum and palladium (Adrangi and Chatrath, 2002), aiming to identify either the degree of co-movement and spillover between them, and/or aiming to identify the leader in the price setting process. However, to get a more reliable picture of the intricate interactions among precious commodities, it is important to include a larger set of such assets and model their interrelationships jointly as a system of equations.

There are only a handful of recent studies that investigate the dynamic interaction among precious metals, crude oil as well as financial variables. Akram (2009), for instance, models the dynamics of crude oil, the US interest rates and exchange rates, and three commodity indices (food, metals, and industrial raw materials). He implements a structural VAR, using a Choleski decomposition of the residuals of the VAR, to identify the structural parameters. He finds that shocks to the interest rate and exchange rate have significant impact on commodity prices, suggesting that exchange rates and interest rates can be used as indicators of future commodity prices. In addition, Akram (2009) documents some degree of overshooting, i.e. the response of commodities to interest rate shocks overreacts at first and later on shows some degree of mean-reversion. Another related study is that of Sari et al. (2010). They examine the dynamic relations between the same assets as we consider in this paper, namely, crude oil, gold, silver, platinum, palladium and the exchange rate and address important questions with regards to which asset is the leader in this set of assets, and which assets follow the leader. Their study documents that there is no cointegration among the various assets; as such there is no long-run equilibrium relation among these assets. Consequently, Sari et al. (2010) continue by modelling the assets under consideration as a VAR and assess the directional impact of one series of an asset on another by considering variance decompositions and impulses response analysis. Their results show that crude oil is rather exogenous, and has little impact on the other assets, and it is not affected much by the other assets. There are, however, relatively strong effects of the precious metals on each other and that the exchange rate predominantly interacts with gold and silver.

Traditionally, the literature has relied on lead/lag dynamic models to study the interrelationship across different markets, in other words, how information from one market affects another one over time. However, the information from one market can affect the other ones instantaneously, in addition to having some delayed effects. Particularly, nowadays where the commodities and financial markets are highly integrated (see e.g., Hong and Yogo, 2012; Hou and Szymanowska, 2013; Boons et al., 2014, among others), the information coming to any market are not only absorbed promptly in that market but in all others as well. As such, it is crucial to differentiate between the two effects, i.e. the contemporaneous as well as lead-lag spillover effects. The literature described above focuses predominantly on modelling the latter effects in commodity prices. The most commonly applied framework in this area is the reduced form VAR, where the dynamic interrelationship can be modelled through lagged effects of one variable on the other. One of the concerns with this approach is that, these reduced form models are often left with a substantial amount of unexplained contemporaneous correlations in the residuals, which essentially captures a relation between variables that cannot be interpreted in a causal way. In a sense, this is the same problem that is observed in simultaneous equation models, in that the contemporaneous causal effects cannot be identified due to the presence of endogeneity among the variables of interest. A common solution to this problem is to use orthogonal structures of residuals such as the Choleski factorization (as in Akram, 2009) or imposing other identifying restrictions. However, orthogonalization or identifying restrictions usually adopted are merely assumptions on the direction of causality or the degree of impact one variable can have on another, which could lead to spurious findings of causation among assets under investigation.

As an alternative way to address the endogeneity issue, Rigobon (2003) puts forth a technique labelled as "identification through heteroskedasticity". This technique employs the heterogeneity in the data to identify the structural parameters in a simultaneous equation model. In a simultaneous equation model, provided there are non-proportional changes in volatility over time, then these changes in volatility affect the underlying relationship among the variables in the model. Finally, these changes in the underlying relationships are then used to identify the structural parameters of the model.

In this paper, we present an empirical study which addresses the issue of causality among the precious metals, crude oil and exchange rates, by employing the Structural VAR technique proposed by Rigobon (2003). In addition, we compare our results with those based on the traditional reduced VAR technique. We highlight that misspecification of causal relationship among precious metals, crude oil and the US dollar based on traditional models could lead to erroneous interpretation and subsequent policy recommendation and/or implementation of erroneous risk management strategies. For instance, we could misinterpret the dynamics between a pairs of metals such as gold-silver and platinum-palladium which do not present lead/lag dynamics according to Granger causality test, ignoring their strong contemporaneous casual relationship.

The remainder of the paper is organized as follows. Sections 2 discusses the data used in this paper. Section 3 details the methodology we employ to identify the contemporaneous relations among the assets. Section 4 presents our empirical findings and their discussions. Section 5 contains our conclusions.

## 2. Data

The analysis in this study is based on daily settlement prices of four precious metal commodity futures (gold, silver, platinum and palladium), crude oil futures and the exchange rate (US dollar to Euro). We collect these prices in US dollars, over the period January 1, 1999 to December 31, 2013 from Thomson Reuters DataStream, giving us a total of 3,762 daily observations per series. From the futures price data, we construct a continuous series, by following the first-nearby contract and rolling this over on the day when trading volume in the second-nearby contract exceeds the volume in the first-nearby contract. From these daily prices, we compute the daily returns as the logarithmic differences in the daily settlement prices.

INSERT TABLE I HERE

In Table I, we report summary statistics for the returns of all series in the sample. Over the sample period, crude oil has the highest average return at 14.07% p.a., followed by gold. The lowest average return is observed for the US dollar (henceforth FX) rate at 1.51%, and the second to lowest return is for palladium. Crude oil, which has the highest average return, also has the highest standard deviation of 38.19%, followed by palladium at 35.13%. The FX rate has the lowest standard deviation followed by gold.[1] The consequence of gold having the second highest average return and the second lowest standard deviation implies that gold has the highest Sharpe ratio (0.5031 p.a.), followed by crude oil (0.3684). The lowest Sharpe ratios are observed for palladium (0.1468) and the FX rate (0.1490), respectively. The distributions of all the metals commodities, except platinum, display negative skewness and all exhibit high kurtosis leading to rejection of the null hypothesis of Normality based on Jarque-Bera statistic. Crude oil also displays negative skewness and excess kurtosis resulting in a non-normal distribution of its returns series. In contrast, the FX rate displays slight positive skewness and excess kurtosis. Although the returns on the FX rate display the lowest degree of skewness and kurtosis, its Jarque-Bera statistics is still highly significant, rejecting

[1]Gold's low volatility is consistent with the fact that gold has a monetary component, and a good portion of its demand goes to hoarding and of its supply comes from recycling.

the null hypothesis of Normality of returns. As expected, all returns are stationary according to ADF unit root test.

INSERT TABLE II HERE

In Table II, we report the Pearson pairwise correlations between the daily returns of assets in our sample. All correlations are positive and significant at the 1% level, ranging between 0.17 and 0.76, with an average of about 0.37. As expected the correlations between the commodities are high. Gold and silver have the highest correlation (0.76). Also, platinum and palladium as members of platinum-group metals have a high correlation of 0.54. On the other hand, the correlations between the precious metals and crude oil are relatively low, ranging from 0.20 to 0.27. Similarly, correlations with the FX rate are relatively low, ranging from 0.17 to 0.34. The existence of positive correlations suggests that there are substantial contemporaneous spillover effects between the precious metals, crude oil and the FX rate.

**3. Identification Strategy**

In this section, we describe the strategy we follow to identify the contemporaneous spillover effects in the Structural VAR (SVAR) that we estimate in this paper. The identification of the contemporaneous spillover parameters builds on the work of Rigobon (2003), and was recently employed by Andersen et al. (2007), Ehrmann et al. (2011), and Chaboud et al. (2014).

To assess the contemporaneous and dynamics spill-over effects between gold, silver, platinum, palladium, crude oil and the FX rate, we implement the following SVAR,

$$A\Delta y_t = c + \Phi(L)\Delta y_{t-1} + \varepsilon_t \,, \tag{1}$$

where $\Delta y_t$ is a (6×1) vector of log returns, i.e. $\Delta y_t$ = ($\Delta gold_t$, $\Delta silver_t$, $\Delta platinum_t$, $\Delta palladium_t$, $\Delta oil_t$, $\Delta FX_t$)', $c$ is a vector of constants and $\Phi(L)$ is a matrix polynomial in the lag operator. The (6×6) matrix $A$ captures the structural parameters, which represent the contemporaneous effects of one variable on another, with the main diagonal normalized to 1, i.e.

$$A = \begin{pmatrix} 1 & \alpha_{12} & \cdots & \alpha_{16} \\ \alpha_{21} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \alpha_{56} \\ \alpha_{61} & \cdots & \alpha_{65} & 1 \end{pmatrix} \tag{2}$$

where, for example, $\alpha_{12}$ measures the contemporaneous impact of silver on gold, while $\alpha_{21}$ measures the contemporaneous impact of gold on silver. All other elements of $A$ are defined likewise. It is important to stress that $\alpha_{12}$ does not have to be the same as $\alpha_{21}$, i.e. contemporaneously the directional effects on one variable on another can differ. We refer to these contemporaneous directional effects as *instantaneous causality*. Also, it is important to point out that the coefficients change sign when the variable moves from the left-hand side of the equation to the right-hand side. Hence, a negative coefficient in the matrix $A$ implies a positive contemporaneous relation, and vice versa.

To estimate the structural parameters in Equation (1), we start by estimating the reduced form VAR, i.e.,

$$\Delta y_t = A^{-1}c + A^{-1}\Phi(L)\Delta y_{t-1} + \eta_t, \qquad (3)$$

where $\eta_t = A^{-1}\varepsilon_t$. We note that traditional literature that relies on a reduced form VAR to model the dynamics is not able to identify the structural parameters in matrix $A$, as they end up in the covariance matrix of the residuals $\eta_t$. However, studies that have aimed to estimate the structural parameters either impose restrictions on the structure of that covariance matrix or make assumptions on the long-run impact of shocks. These assumptions are quite often restrictive or ad hoc in that they either assume a direction of causality, or whether a variable has a long-run impact on another variable or not.

In this paper, we follow the identification strategy of Rigobon (2003) to determine the structural parameters in $A$. As with the previous approaches, we need to impose some conditions to achieve identification of these parameters. The first condition is that $\varepsilon_t$, the residuals in Equation (1), represent structural shocks to the model and that these structural shocks are uncorrelated with each other. This implies that all contemporaneous correlation between the assets in the reduced form VAR originate from the structural parameters in $A$. The second condition is that the assets display time-varying volatility, i.e. heteroskedasticity. This feature is commonly observed among these assets (see e.g. Yang and Brorsen,1993; Plourde and Watkins, 1998; and Adrangi and Chatrath, 2002; among others), while the parameters in the matrix $A$ remain constant across the different heteroskedasticity regimes, i.e. all heteroskedasticity comes from time-varying volatility in the structural residuals. These two assumptions allow us to identify the structural parameters in $A$.

Identification of the structural parameters in $A$ can now be achieved by focusing on the reduced form residuals $\eta_t$. In the case where there is no heteroskedasticity in $\varepsilon_t$, there would also be no heteroskedasticity in $\eta_t$. As such, the covariance matrix of the reduced form residuals is given as $\mathrm{Var}(\eta_t) = A^{-1}\mathrm{E}[\varepsilon_t\varepsilon_t']A^{-1\prime} = \Omega$, which contains 21 unique elements (6 variances and 15 covariances). Likewise, we can define the covariance matrix of the structural residuals as $\mathrm{Var}(\varepsilon_t) = \Sigma$, which is a diagonal matrix following the first condition that the structural shocks are independent. Given that $A$ contains 30 elements and $\Sigma$ contains 6 elements, full identification of Equation (1) cannot be achieved (we observe only 21 moments, the elements of $\Omega$, but have 36 parameters to identify). This is exactly the reason why the reduced form VAR cannot identify the structural parameters. Hence the model is underidentified.

In the case where there is heteroskedasticity in the residuals, we can identify additional volatility regimes, i.e. we could introduce a second, say, high volatility regime, and based on the two regimes, we could compute two covariance matrices in the reduced form VAR, $\Omega_1$ and $\Omega_2$. Combined these two matrices provide 42 moments for estimation. Similarly, we have 42 parameters to be identified, i.e. 30 structural parameters in $A$ and 12 variances in $\Sigma_1$ and $\Sigma_2$. Hence in the case of two regimes the model would be exactly identified. We could introduce further regimes if desired to achieve overidentification.[2]

[2]Rigobon (2003) points out that the identification through heteroskedasticity is a very robust technique, as it is not sensitive to misspecification of the actual conditional volatility process. All that the technique requires is

In our empirical setting, we implement the identification strategy in a way similar to Ehrmann et al. (2011). We start by estimating the reduced form VAR and collect the residuals $\eta_t$. These residuals contain the contemporaneous effects (i.e. $\eta_t = A^{-1}\varepsilon_t$) and we use these residuals to estimate the structural parameters in $A$. To determine the volatility regimes, we calculate the variance of the residuals using a 22-day rolling window (roughly a 1-monthly variance) over the entire sample period. Next, we assign the data of a particular series to a high volatility regime if its variance is higher than its mean plus one standard deviation. Doing so, we construct 6 high volatility regimes, where each of the assets in our sample sits in a high volatility regime while the rest of the series are in the low volatility regime, and one tranquil regime where all series are in a relatively low volatility regime.[3] The use of these 7 regimes to identify the parameters in $A$ ensures that we will have non-proportional shifts in the volatility of one asset versus the other assets, which is a requirement for identification.

Finally, we estimate the parameters by the Generalized Method of Moments (GMM) method of Hansen (1992) by solving the problem: $\min g'g$, where $g = A^{-1}\Sigma_i A^{-1\prime} - \Omega_i$ with i = 1,…, 7 regimes. We further compute confidence intervals on the coefficients in matrix $A$ by implementing a block-bootstrap procedure based on Ehrmann et al. (2011). Specifically, for each of the 7 regimes we simulate pseudo residuals for that regime that has the same

non-proportional shifts in the volatility of the residuals. In fact the volatility process could be modelled as a multivariate GARCH process (Rigobon and Sack, 2003) or estimation could be done using a regime-switching model (Lanne and Lütkepohl, 2010).

[3]We perform Breusch-Pagan tests for heteroskedastcity in the residuals of the reduced form VAR. We find the residuals reject the null hypothesis of homoskedasticity at the 1% level for all series. These results are available on request.

covariance structure as the actual residuals. We then use the estimated coefficients of the reduced form VAR to compute the pseudo-data $y_t^*$. With this pseudo-data, we re-estimate the VAR and keep the residuals, $\eta_t^*$. We use these bootstrapped residuals to identify new regimes and estimate the matrix $A^*$ based on these bootstrapped residuals. We repeat this procedure 1,000 times and store the critical values for the point estimates of matrix *A*.

## 4. Empirical Results

In this section, we present the results for the model developed in Section 3. We start by estimating a reduced form VAR and present results for the lead-lag dynamics. Second, we use the residuals from the reduced form VAR to obtain the structural parameters in matrix *A* shown in (2), and document these results. Finally, we compare the results based on Impulse Response Functions (IRFs) for the reduced form to IRFs for the Structural VAR.

### *4.1. Granger and Instantaneous Causality*

We start our analysis by estimating a reduced form VAR for the four metal commodities, crude oil and the FX rate. Similar to Sari et al. (2010), we include dummy variables to control for the establishment of the oil price band by OPEC in 2000, the 9/11 New York City attack, and the 2003 Iraq war. Following standard procedure, we use the Akaike Information Criterion to determine the optimal lag length, which turns out to be 2 lags in our case. From the reduced form VAR, we obtain parameter estimates and compute Granger causality statistics.

In Table III, we report the Granger causality statistics for the different series, where the columns represent the series from which the causality is running and the rows represent the series towards which the causality is running. When we consider the first column, which reports the causal effect of gold on the other assets, we observe that gold only has a significant effect on the exchange rate, and no spillover to the other commodities. A similar result is found for silver, with a significant effect on the FX rate, but no effect on other commodities. It is interesting to point out that there are no causal effects in either direction between gold and silver. Considering platinum and palladium, we observe that these series have no impact on the other commodities and the FX rate. Again, there is no bi-directional causality between the platinum-palladium pair. Crude oil has a significant causal effect on silver and platinum, which highlights the importance of oil and its spillover effect on these commodities. However, we observe no spillover of crude oil on the FX rate. Finally, we report the Granger causality of the FX rate on the other series. We observe that there is no causality from the FX rate to any commodity, suggesting that the FX rate is relatively exogenous to these series.

INSERT TABLE III HERE

The Granger causality statistics show the lead-lag relations between the different series. However, these lead-lag relations may not capture the full causal effects of one series on another. For example, Table III documents that there are no causal relations between gold and silver, whereas Table II documents a contemporaneous correlation of 0.76, suggesting that the series are strongly related to each other. The same holds for the platinum-palladium pair. It also suggests that while there may not be any spillover between lags of the series, there may be spillovers at the contemporaneous level. These contemporaneous spillover effects can be deduced from the matrix *A* as described in Section 3.

In Table IV, we report the structural parameters in matrix *A*, along with their 95% critical values in brackets, which we obtain by using the bootstrap procedure. From this table, we can make several noteworthy observations. First, we note that gold has a strong positive contemporaneous effect on silver (note that signs on the coefficients are reversed as the matrix *A* sits on the left hand side of Equation (1)). In addition, we observe a significant positive effect of gold on platinum. These findings are interesting in light of the earlier Granger causality findings reported in Table III, which showed that gold did only Granger cause to FX rate. This demonstrates that the reduced-form VAR is not able to pick up important aspects of the interactions between these commodities.

INSERT TABLE IV HERE

For silver, we note that there is a contemporaneous positive spillover to gold. However, the magnitude of the spillover in this direction is much smaller than the contemporaneous spillover from gold to silver. We also observe that the confidence intervals for gold and silver do not overlap, and hence conclude that the impact of gold on silver is significantly larger than the impact of silver on gold, and thus that gold is the informational leader in this pair of commodities. Silver further has a significantly positive effect on platinum, palladium and crude oil. Once again we observe how the reduced-form VAR did not pick up these spillover effects, given that none of the spillovers from silver to the other commodities were observed in the lead-lag dynamics captured by the Granger causality statistics.

When we consider the pair of platinum and palladium, there are positive contemporaneous spillovers from both of them to each other. However, the effect of platinum on palladium is much stronger than the reverse spillover, and again the confidence intervals do not overlap suggesting that platinum is the leader in the pair of these commodities. As in the case of gold and silver, we found no Granger causality between platinum and palladium in Table III, suggesting that the reduced form VAR is not able to pick up these spillover effects. Both platinum and palladium have no contemporaneous effects on the other assets.

We find no evidence of contemporaneous spillovers from crude oil to any of the other assets. These results again contrast those findings in Table III, which documents strong Granger causal effects of crude oil on silver and platinum. This suggests that the information in crude oil spills over to the other assets, but does so with a lag. Finally, we observe a positive contemporaneous spillover from the FX rate to gold, but no spillover effects to other commodities.

### *4.2 Impulse Response Functions*

In the previous section, we demonstrated the stark differences in causality that is observed through dynamic lead-lag relations and through contemporaneous relations. These differences also have a material impact on forecasts that we obtain when applying shocks to the VAR. We can describe the forecasts based on shocks by considering impulse-response functions.

These IRFs are the outcomes of experiments, where shocks are applied to series, and the outcomes of these shocks are measured as they progress through the VAR.

A common issue with IRFs is that it is often not clear what shock needs to be applied. One could apply a unit shock to only one series, but this ignores the correlations among the series, and would not give a realistic reflection of the impact of a shock on one series on the others. Likewise, taking the correlation between the series into account ignores the fact that while the series may be correlated, it is not clear how causality runs between the series. Hence, not knowing the structural relations between the variables will make the application of a correct shock difficult. The traditional solution to this problem is to rely on a Choleski decomposition of the covariance matrix of the residuals of the reduced-form VAR, i.e. assuming that Ω = PP', where P is a lower triangular matrix (see for example Akram, 2009). However, the outcomes of the impulse-response functions based on the Choleski decomposition depend on the ordering of the variables in the VAR, and merely make an assumption on the direction of causality. An alternative and frequently used solution is to use Generalized Impulse Response functions (GIR) due to Koop et al. (1996) and Pesaran and Shin (1998). These GIRs are not affected by the ordering of the variables in the VAR, and incorporate the correlation structure in Ω. However, the GIRs do not use the actual contemporaneous relations between the variables to define the shocks in the impulse response function, as matrix *A* remains unidentified in the reduced form VAR and thus the GIR.

Given that our identification through heteroskedastcity approach is able to uniquely identify the matrix *A*, we also know the exact structure of the covariance matrix of the residuals in the reduced form VAR, i.e. $\Omega = A^{-1}\Sigma A^{-1}{}'$. The knowledge of this exact structure provides us with a unique vector of initial shocks that are to be applied in the impulse response functions, where a unit shock to the $j^{\text{th}}$ element of $\varepsilon_t$ is defined as

$$E(\eta_t \mid \varepsilon_{jt} = 1) = \frac{A^{-1} e_j}{A_{jj}^{-1}},$$

where $e_j$ is a (6×1) vector of which the $j^{\text{th}}$ element is equal to one and all other elements are zero. We refer to the impulse response functions based on the structural VAR as the Structural Impulse Response functions (SIRs).

In Figure 1, we plot the cumulative impulse response functions up to 10 steps ahead, where we show the GIR in the left column and the corresponding SIR in the right column. A unit shock is applied to the series labelled above each plot. The first plot shows the impact of a shock to gold. We can observe some differences between the results for the GIR and the SIR, where according to the SIR a shock in gold has a less strong impact on platinum, palladium, crude oil and the FX rate, compared with what the GIR would attribute. According to the SIR, shocks to gold have a slightly higher impact on silver then what the GIR would attribute.

Next, we show the results for silver. According to the GIR, a shock in silver has an important and immediate impact on gold. However, the SIR shows that the impact of silver on gold is weak. According to the SIR, the most important impact of a shock in silver is on palladium, whereas the GIR sees the strongest impact (besides gold) on platinum. In addition, the GIR suggests that a shock in silver has a notable impact on the FX rate, while the SIR shows that this impact is marginal.

For shocks to platinum, we again note clear differences in the impulse response functions. According to the GIR, a shock to the price of platinum leads to a reaction in gold, silver, and palladium of about the same magnitude. According to the SIR, however a shock in platinum only affects the price of palladium in a substantial way. The responses of the other commodities to shock in platinum are marginal. When considering a shock in the price of palladium, we observe that according to the SIR there is almost no reaction in the other assets, besides a marginal reaction in platinum. However, the GIR suggests strong reactions in many of the other commodities.

A shock in the price of crude oil has virtually no impact on the other assets in the sample according to the SIR. However, the GIR documents a marginal reaction in all assets due to a shock in the price of crude oil. Finally, as for the FX rate, we note that SIR documents strong reaction in all commodities except for the price of oil. The GIR underestimates the reaction of the commodities to a shock in the FX rate.

The results from the impulse-response functions demonstrate clear differences in the impact of shocks on other commodities when basing the shocks on a structural versus a reduced form VAR. In Table 5, we report the results for the long-run impact of a unit shock to each series by reporting the 100-step ahead cumulative impulse response function. To make a comparison with the traditional approach based on the reduced form VAR, we report the results for the GIR in Panel A, and the results for the cumulative impulse-response function based on the Structural VAR (SIR) in Panel B. In each column of this table, we report the results of a unit shock to the variable in this column on all assets under consideration. The results show that there can be considerable differences between the outcome according to the GIR and according the SIR.

INSERT TABLE 5 HERE

When we compare the results for a unit shock applied to gold, we observe that in the structural model the impact on silver is larger than what we observe according to the GIR, whereas the impact of a shock to gold on platinum, palladium, crude oil and the FX rate are smaller according to the SIR than what they are according to the GIR. Next, we consider shocks to silver, we first note the difference between the GIR and SIR for the impact of a shock in silver on gold. According to the SIR the long-run impact of a shock in silver on gold is 0.15, while according to the GIR this is 0.77. In addition, according to the GIR the long-run impact of silver on gold is slightly larger than the impact of gold on silver. The SIR shows a much larger impact of gold on silver than the reverse. These findings clearly establish the differences that occur between the reduced form and the Structural VAR and show that shocks in silver have a much lower impact on gold when one properly incorporates the contemporaneous interrelationship between the two. According to the SIR, shocks in silver have a much lower impact on platinum than what the GIR attributes, and also a slightly lower impact on palladium. Finally, we note that shocks in silver, according to the SIR, have a very small impact on the FX rate, while the GIR suggests that there is quite a strong impact.

Next, we consider the impact of shocks in platinum. We once more observe notable differences. According to the SIR, shocks in platinum have virtually no impact on gold, silver, and the FX rate, whereas the GIR suggest that there would be quite strong impacts. The impact of a shock in platinum on palladium is about the same under both GIR and SIR, while the impact of platinum on crude oil according to the SIR is almost a half of what it is based on the GIR.

We next turn to the impacts of a unit shock to palladium, which are reported in the next column. According to the SIR, shocks to palladium have virtually no impact on gold, silver, crude oil and the FX rate. This is in stark contrast to what is suggested by the GIRs. According to the SIR, shocks in palladium have some impact on platinum, but is less than a third of the impact that is suggested by the GIR. When looking at the platinum-palladium pair, we observe that, according to the SIR, platinum has a much stronger impact on palladium than the reverse. According to the GIR, both affect each other to similar degrees. For the impact of crude oil on the other commodities and the exchange rate, we observe that for all other commodities and the FX rate, the impacts of shocks to crude oil are much smaller according to the SIR, than the impacts according to the GIR. Finally, according to the SIR, shocks to the FX rate have a much stronger effect on the precious metals than what is suggested by the GIR. However, according to both the GIR and the SIR, shocks to the FX rate have a relatively small impact on crude oil.

## 5. Conclusions

We investigate the concurrent interrelationship among precious metals, crude oil and the US dollar exchange rate. Using daily data for the period January 1, 1999 to December 31, 2013, we compare and contrast the results obtained by applying the conventional reduced form VAR (based on lead/lag relationships) and the Structural VAR (based on contemporaneous relationship). We demonstrate that by not taking into consideration the contemporaneous interrelationships among precious metals, crude oil and exchange rate, leads to inaccurate outcomes and consequentially in interpretation of causal relationships among these assets that could be far off the mark.

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## Table I. Summary Statistics over the Sample Period

| | Gold | Silver | Platinum | Palladium | Crude oil | FX US$/EUR |
|---|---|---|---|---|---|---|
| Average (p.a) | 9.57% | 9.08% | 8.87% | 5.16% | 14.07% | 1.51% |
| Std. Dev. (p.a.) | 19.02% | 32.46% | 25.00% | 35.13% | 38.19% | 10.17% |
| Sharpe ratio (p.a.) | 0.5031 | 0.2797 | 0.3549 | 0.1468 | 0.3684 | 0.149 |
| Skewness | -0.1465 | -0.9479 | 0.4077 | -0.7065 | -0.2121 | 0.1666 |
| Kurtosis | 9.1094 | 10.5728 | 18.9737 | 12.0924 | 7.2531 | 5.3749 |
| ADF test | -12.12*** | -11.98*** | -9.82*** | -9.81*** | -10.65*** | -10.65*** |
| Jarque-Bera | 5864.16*** | 9552.46*** | 40100.45*** | 13271.82*** | 2863.62*** | 901.46*** |

Note: this table provides summary statistics of the various series over the sample period 1 January 1999 to 31 December 2013. We report the annualized average returns, annualized standard deviation, and annualized Sharpe ratio. In addition, we report skewness, kurtosis, ADF unit root test and the Jarque-Bera statistic, which tests whether the series follow a Normal distribution. *** indicates significance at the 1% level.

## Table II. Contemporaneous Correlations

| | Gold | Silver | Platinum | Palladium | Crude oil | FX US$/EUR |
|---|---|---|---|---|---|---|
| Gold | 1 | | | | | |
| Silver | 0.7580 | 1 | | | | |
| Platinum | 0.5072 | 0.5153 | 1 | | | |
| Palladium | 0.3992 | 0.4645 | 0.5435 | 1 | | |
| Crude oil | 0.2413 | 0.2692 | 0.2298 | 0.1992 | 1 | |
| FX US$/EUR | 0.3444 | 0.3297 | 0.2656 | 0.2532 | 0.1659 | 1 |

Note: This table reports the contemporaneous correlation coefficients between all series in the sample. All correlations are significant at the 1% level.

## Table III. Granger Causality between Precious Metals, Crude Oil and the FX Rate

| | Gold | Silver | Platinum | Palladium | Crude oil | FX US$/EUR |
|---|---|---|---|---|---|---|
| Gold | | 1.4611 | 2.4380 | 0.9452 | 1.8941 | 1.9249 |
| Silver | 2.5559 | | 0.5114 | 3.2905 | **10.6909*** ** | 3.0191 |
| Platinum | 1.3970 | 3.2390 | | 3.7575 | **8.3232** ** | 0.9349 |
| Palladium | 2.9414 | 2.1563 | 2.3383 | | 3.2459 | 1.2196 |
| Crude oil | 1.1115 | 2.3373 | 2.3218 | 0.2470 | | 2.7609 |
| FX US$/EUR | **11.2757*** ** | **7.4870** ** | 0.1598 | 3.6483 | 0.2882 | |

Note: This table reports Granger Causality statistics based on a HAC-consistent Wald statistic. The columns represent the series from which causality is running, whereas the rows represent the series towards which causality is running. Significance at the 10%, 5%, and 1% levels are indicated by *, **, and ***, respectively.

## Table IV. Contemporaneous Spillover Effects

| | Gold | Silver | Platinum | Palladium | Crude oil | FX US$/EUR |
|---|---|---|---|---|---|---|
| Gold | 1 | **-0.1266** | -0.0054 | -0.0396 | -0.0279 | **-0.5366** |
| | | [-0.2002, -0.0645] | [-0.1075, 0.0811] | [-0.0890, 0.0170] | [-0.0662, 0.0196] | [-0.6940, -0.1868] |
| Silver | **-0.7681** | 1 | -0.0588 | -0.0051 | 0.0293 | -0.1301 |
| | [-0.9600, -0.5694] | | [-0.2245, 0.0936] | [-0.0870, 0.0853] | [-0.0565, 0.1190] | [-0.8995, 0.5696] |
| Platinum | **-0.2473** | **-0.1912** | 1 | **-0.1091** | 0.0265 | 0.058 |
| | [-0.4199, -0.0889] | [-0.2840, -0.0890] | | [-0.1868, -0.0321] | [-0.0433, 0.1103] | [-0.3582, 0.6488] |
| Palladium | 0.2132 | **-0.3279** | **-0.478** | 1 | 0.0535 | -0.5472 |
| | [-0.0858, 0.5152] | [-0.5255, -0.1532] | [-0.7054, -0.2654] | | [-0.2471, 0.3414] | [-1.2465, 0.6448] |
| Crude Oil | 0.1481 | **-0.3111** | -0.09 | -0.0746 | 1 | -0.1233 |
| | [-0.2153, 0.5045] | [-0.5688, -0.0527] | [-0.4430, 0.2070] | [-0.3942, 0.3120] | | [-1.3386, 0.8715] |
| FX US$/EUR | -0.0055 | -0.0437 | -0.0153 | 0.016 | -0.0004 | 1 |
| | [-0.1409, 0.0222] | [-0.0891, 0.0369] | [-0.0844, 0.0650] | [-0.0686. 0.0707] | [-0.0631, 0.0691] | |

Note: This table reports the coefficients for the contemporaneous spillover effects. Each column represents the series from which the spillover occurs, whereas each row represents the series towards which the spillover goes. We assess the significance of the spillover by following the bootstrap procedure detailed in Appendix A, and report the 95% critical values in brackets. Coefficients significant at the 5% level are printed in bold.

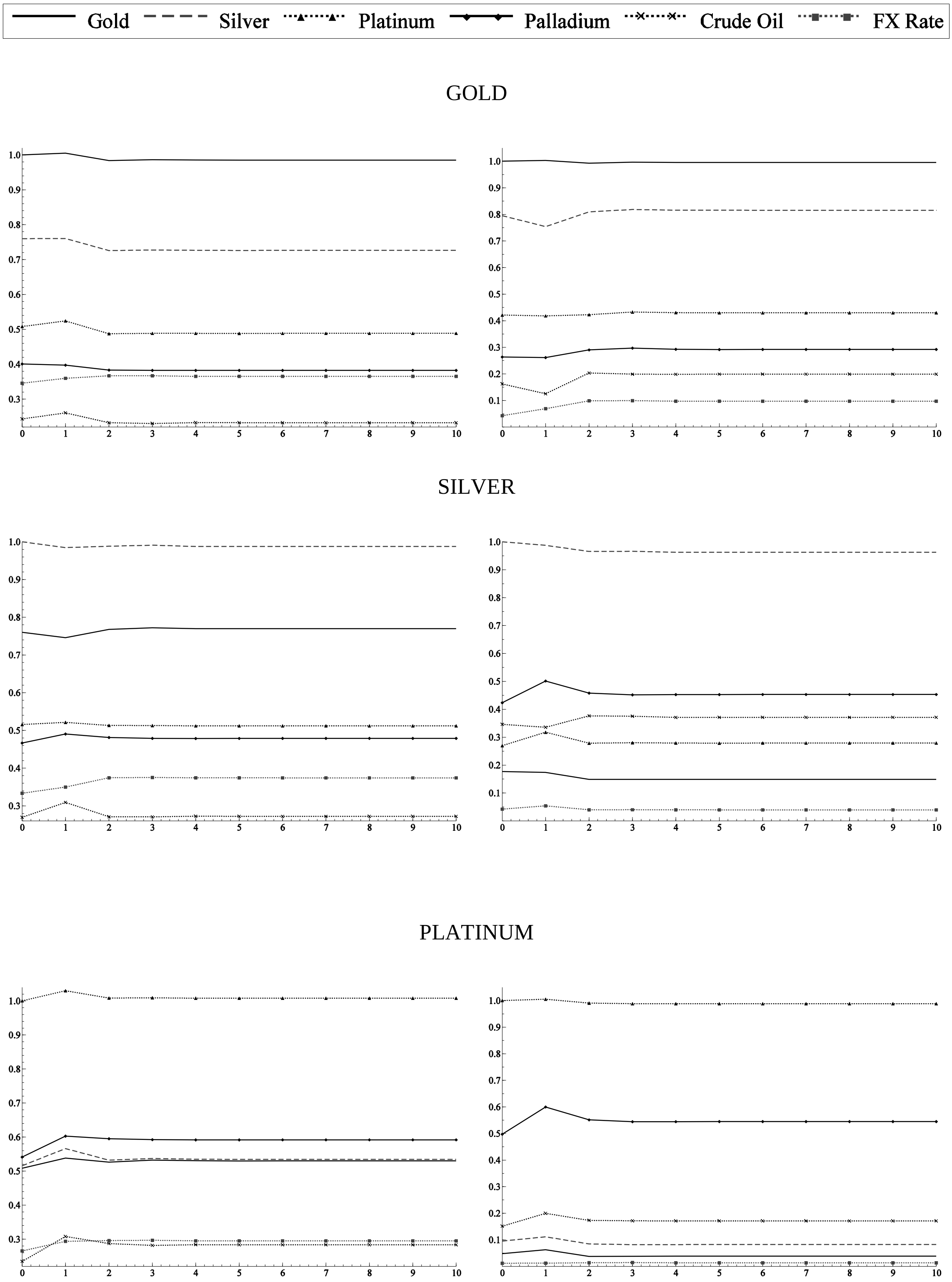
**Table V. Long-Run Impact of Shocks**

| | Gold | Silver | Platinum | Palladium | Crude oil | FX US$/EUR |
|---|---|---|---|---|---|---|
| Panel A: Generalized Impulse Response | | | | | | |
| Gold | 0.9850 | 0.7697 | 0.5299 | 0.4259 | 0.2577 | 0.4268 |
| Silver | 0.7263 | 0.9877 | 0.5345 | 0.4949 | 0.2916 | 0.3748 |
| Platinum | 0.4885 | 0.5119 | 1.0078 | 0.5806 | 0.2497 | 0.2979 |
| Palladium | 0.3824 | 0.4787 | 0.5917 | 1.0472 | 0.2030 | 0.2628 |
| Crude oil | 0.2324 | 0.2722 | 0.2835 | 0.2313 | 0.9386 | 0.1924 |
| FX US$/EUR | 0.3651 | 0.3741 | 0.2949 | 0.2453 | 0.1513 | 0.9995 |
| Panel B: Structural Impulse Response | | | | | | |
| Gold | 0.9950 | 0.1487 | 0.0385 | 0.0364 | 0.0225 | 0.7113 |
| Silver | 0.8154 | 0.9626 | 0.0821 | 0.0557 | -0.0111 | 0.8083 |
| Platinum | 0.4296 | 0.2789 | 0.9882 | 0.1661 | -0.0045 | 0.3789 |
| Palladium | 0.2917 | 0.4529 | 0.5450 | 1.0440 | -0.0613 | 0.6974 |
| Crude oil | 0.1989 | 0.3711 | 0.1710 | 0.0819 | 0.9268 | 0.2393 |
| FX US$/EUR | 0.0972 | 0.0396 | 0.0135 | -0.0147 | 0.0060 | 1.0041 |

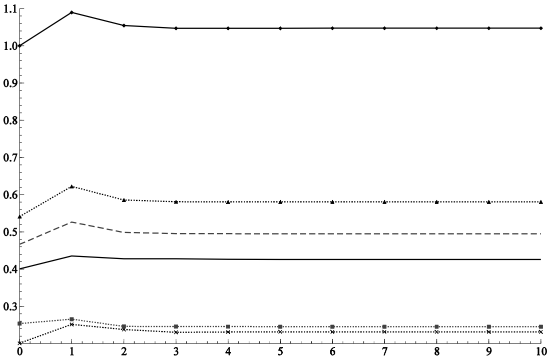
Note: This Table reports the long-run impacts of shocks, measured by the cumulative impulse response function after 100 steps. Unit shocks are applied to the asset listed in a column and the long-run effect of that shock is reported in each row. Panel A reports the results for the long-run impact of the Generalized Impulse Response functions, whereas Panel B reports the results for the Impulse responses based on the Structural VAR.

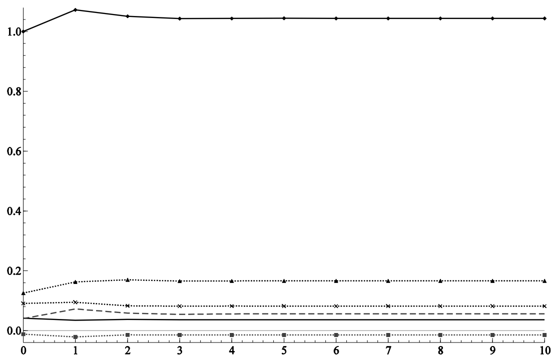
**Figure 1. Impulse Response Functions**

The graphs show the impacts of unit shocks the series specified above the graph. The left column plots the GIR based on the reduced form VAR, whereas the right column plots the SIR based on the structural VAR.



## PALLADIUM





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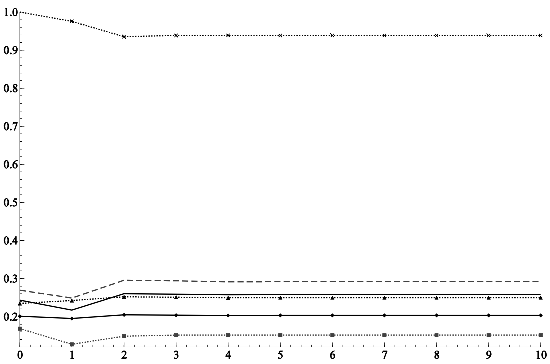

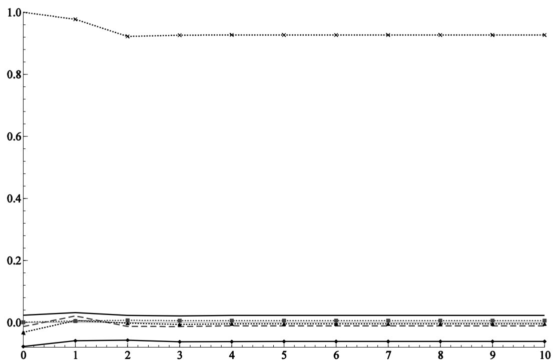

## FX RATE