The volatility effect on precious metals prices in a stochastic volatility in mean model with time-varying parameters

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Abstract

We use the time-varying parameter stochastic volatility (TVP-SV) model and monthly data from 1962 to 2017 to examine the effect of uncertainty in the precious metal markets (gold, silver, platinum, and palladium). We find evidence that uncertainty has a largely time-varying impact on the precious metal prices. The results also show significant variation in the level of volatility, with high volatility being associated with periods of large volatility shocks corresponding to known historical events. The results show that uncertainty has a significant negative impact on the precious metal prices and the impact is more negative during higher volatility periods, implying that large volatility increases cause crashes in the precious metals markets. The market volatility is also found to be extremely persistent, implying that strong policy measures might be required to restore equilibrium. The estimates also show that price level has a positive and significant effect on the volatility and, thus, higher precious metal prices generates increased future uncertainty.

Keywords: Precious metals; Uncertainty; Stochastic volatility; State–space.  
JEL Codes: C22, E31

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1. Introduction

It has been known for a long time in the literature that one of the fundamental determinants of commodity prices is the dynamic links between such basic macro-economic factors such as the demand, exchange rates, input prices and production processes (Soytas et al., 2009; Abbott et al., 2009). Besides, the financialization of commodity markets have exposed commodity prices to various financial market shocks (Tang and Xiong, 2012; Cai et al., 2001; Christie-David et al., 2000; Fama and French, 1988). All these dynamics show that macro-economic factors affecting, particularly, financial markets can have effects on commodity prices. In contrast to other commodities, traditional perception of precious metals is that they offer valuable diversification opportunities to investors and serve as a monetary instrument when there is uncertainty in markets and, thus, they have the safe haven function against inflation (e.g., Arouri et al., 2012; Batten et al., 2010; Baur and Lucey, 2010; Christie-David et al., 2000; Ciner, 2001; Heemskerk, 2001). For this reason, the price of precious metals is considered as the major indicator of inflation or as a variable capable of transmitting the outlook of monetary policy into economy (Greenspan, 1993). In other words, the pro-cyclical characteristic of precious metals can emphasise their roles as safe haven and store of values, giving them ability to provide considerable information on the direction where economy is progressing.

It is known that macroeconomic and financial variables display certain statistical properties which can have impacts on policy makers, investors, manufacturers, consumers, researchers and portfolio managers. One of those properties which is remarkable is structural breaks or regime switching (Stock and Watson, 1996; Ang and Bekaert, 2002; Gil-Alana et al., 2013). Historically, commodity prices have been characterised by upward and downward trends. These dynamics observed in commodity prices suggest that volatility is an important characteristics of commodity prices (Kroner et al., 1995; Brunetti and Gilbert, 1995; Pindyck, 2004; Gilbert, 2006; Fernandez, 2008). Calvo-Gonzalez et al. (2010) and Deaton and Laroque (1992) refer to volatility as a source of structural breaks. It may be stated that precious metal markets are particularly very sensitive to fluctuations in supply, demand and in other macroeconomic aggregates (Radetzki, 1989; Batten et al., 2010; Hammoudeh et al., 2010). In addition to that, geopolitical tension, the Gulf Wars, Asian crisis, concerns about Iran’s nuclear plans and current global weaknesses can also cause sudden falls in the price of precious metals (Arouri et al, 2012). These dynamics can cause sudden breaks in the price of
precious metals. If structural breaks in precious metal prices are ignored, there may arise concerns about the in sample fit and out of sample forecasting performance of models due to the existence of higher order unconditional moments such as kurtosis, skewness and tail fat tails (Mikosch and Stărică, 2004; Pesaran and Timmermann, 2004). Several previous studies analyzed the dynamic properties of the price of precious metals. One of such studies is the one performed by Gil-Alana et al. (2015). Gil Alana et al (2015) examined the long-memory dynamics of precious metals by taking the structural breaks in the price of gold, silver, rhodium, palladium and platinum into consideration. They demonstrated that structural breaks existed in the price of precious metals except for the price of palladium. Yet, after accounting for structural breaks, evidence of an increase in the degree of persistence across time in the majority of cases has been found, which implies that in general, shocks to these precious metals will be long lasting or permanent and require strong policy measures to restore equilibrium levels in the event of, particularly negative, shocks. Recently, Balcilar and Ozdemir (2017) investigate the dynamic nexus between oil price and its volatility by a stochastic volatility in mean model with time-varying parameters approach. Estimation results obtained from the study of Balcilar and Ozdemir (2017) show that the impact of uncertainty on commodity prices return negative during these large positive shock periods. This result puts forward that commodity price hikes in these periods are reversed. This evidence can be interpreted as the sign of the start of a declining trend in oil prices following the price hikes. A similar behavior in stock markets in which market crashes follow large volatility shocks has been seen in the literature on financial markets. Thus, this study investigates the dynamic nexus between precious metal prices and their volatility using a stochastic volatility in mean model with time-varying parameters approach.

The basic issues in analyzing stochastic models in relation to commodity prices include time varying trends, convenience yields and volatilities, and mean reversion. Some of the studies investigating the time series properties of commodity prices in the literature are the one by Gibson and Schwartz (1990), Schwartz (1997), Pindyck (1999), Schwartz and Smith (2000), Cortazar and Schwartz (2003), Beck (2001), Saphores et al. (2002) and Khalaf et al. (2003). Auto-regressive conditional heteroscedasticity (ARCH) model and the extensions of the ARCH model (EGARCH, CGARCH, IGARCH, AGARCH, DECO-GARCH, etc.) have been used in the literature to model the volatility of precious metals and to forecast volatility. The studies available in the literature used the univariate and multivariate forms of those models depending on their purpose. Vivian and Wohar (2012) and Watkins and McAleer
(2008) are examples for studies employing univariate GARCH models. Hammoudeh and Yuan (2008), Morales and Andreosso-O’Callaghan (2014), Papadamou and Markopoulos (2014), Charlot and Marimoutou (2014), Bunnag (2015), Bosch and Pradkhan (2015) and Kang, McIver and Yoon (2017), on the other hand, are the examples studies using multivariate GARCH models. The most important feature of univariate and multivariate GARCH models used in modelling the price of precious metals is that their parameters are assumed to have constant coefficients, they impose certain higher order moment restrictions on the process, and require parameter restrictions to guarantee a positive conditional variance.

As it is clear from the previous studies available in the literature, most economic and financial time series display structural instability (also see, for instance, Canova 1993; Cogley and Sargent 2001; Koop and Potter 2007). A method commonly used in modelling this structural instability is the time-varying parameter (TVP) model. In such models, parameters in conditional mean can change through time. Studies conducted recently on time series emphasize the importance of time-varying volatility in macroeconomic and financial time series and its contributions to the literature. In such models, heteroscedastic errors are usually modelled by using stochastic volatility specification (see, for instance, Cogley and Sargent 2005; Primiceri 2005). It was demonstrated in D’Agostino et al. (2013) in relation to macroeconomic forecasts that both structures were determinants for generating precise forecasts. Chan (2017) developed univariate time series model with time varying parameters and stochastic volatility in order to investigate the time-varying effects of stochastic volatility on the level of the series. The model developed by Chan (2017) is based on Koopman and Hol Uspensky’s (2002) volatility in mean (SVM) model. Koopman and Hol Uspensky’s (2002) volatility in mean (SVM) model was, indeed, developed for financial time series as an alternative to Engle et al. (1987) ARCH-M model. Following the study of Chan (2017), our study is the first in the literature that considers time-varying impact of uncertainty of the precious metal prices on the precious metal prices. Building on the Bayesian TVP-SVM model approach of Chan (2017) and allowing time-varying uncertainty effect on the precious metal prices, this approach optimally allows time-varying impact and therefore robustly accounts for structural breaks in the precious metal market.

This study aims to analyze the dynamic relationships between the price of precious metals such as gold, silver, copper, platinum and palladium and volatility. It uses the time varying parameter stochastic volatility in mean (TVP-SVM) model for this purpose. The
TVP-SVM model allows us to investigate how the precious metals price volatility affects the level of precious metals price and vice-versa. Extensive literature investigating the correlations between the price of precious metals and their volatility is available. In contrast to previous studies considering models having only constant coefficients in conditional mean, time-varying parameter model enables us to investigate whether or not the relationship between precious metals price and uncertainty of precious metals’ price change over time. The data used in this study are the monthly return of precious metals traded on London Precious Metals Market obtained from the closing price of US Dollars. This study makes three important contributions to the literature. First, it analyses the effects of time-varying uncertainty of precious metals price series on precious metals price series by using the TVP-SVM model for such precious metals price series as gold, silver, copper, platinum and palladium for the first time to the best of our knowledge. TVP-SVM approach models time-varying effects in the best way and therefore it endogenously incorporates structural breaks robustly. Second, while this approach, which is based on the SVM model, considers uncertainty shocks in a stochastic approach, the previously used GARCH models examine volatility series deterministically. Thus, this study is different from others available in the literature in the way it models the volatility effect by allowing uncertainty shocks in the volatility model. Third, our approach also allows us to investigate the effects of precious metal prices on their own volatility. The prices of metals with high and low values have different market conditions. Therefore, these dynamics are likely to influence the volatility of precious metals. The basic findings obtained in this study suggest that considerable time-varying effects exist in the coefficients, implying that the effects of uncertainty on precious metal prices are subject to structural breaks or regime shifts. It was also found that uncertainty affects the price of precious metals in negative ways throughout the period. The results also demonstrated that the coefficient related to lagged precious metal return series in the volatility equations were positive and significant for gold, silver, copper, platinum, palladium and palladium metal price series. This means that changes in level of precious metal prices have positive and effects on volatility, meaning that periods with higher metal prices are accompanied with higher price uncertainty and low metal price periods cause reduced are also the periods of reduced volatility.
2. Methodology

Recent literature has demonstrated that many macroeconomic time series show structural instability (see Stock and Watson 1996; Cogley and Sargent 2001, among many others). An optimal approach for modelling structural instability is the TVP approach in which some parameters of a model evolve over time in stochastic manner. In this paper, we allow the impact of metal price uncertainty on the metal price to be time-varying, capturing any structural instability in the macroeconomic environment that may alter the price-price uncertainty relationship. Although, there are several approaches to measure metal price uncertainty, a popular approach is the stochastic volatility (SV) model of Koopman and Uspensky (2002), which usually fits better to time series that show conditional heteroskedasticity. Compared to the GARCH models, where the volatility specified with a deterministic function, volatility in the SV models is specified as a latent stochastic process that allows volatility shocks. In this paper, following Chan (2017), we combine the TVP and SV approaches in analyzing the metal price and metal price uncertainty (volatility) relationship, as a flexible model that robustly allows structural breaks and stochastic volatility shocks. Additionally, we allow the past metal price to affect the oil price uncertainty. The TVP-SVM model is specified as follows:

\[ y_t = \tau + \alpha_t e^{ht} + \varepsilon_t^y, \quad \varepsilon_t^y \sim \mathcal{N}(0, e^{ht}) \]  
\[ h_t = \mu + \phi(h_{t-1} - \mu) + \beta y_{t-1} + \varepsilon_t^h, \quad \varepsilon_t^h \sim \mathcal{N}(0, \sigma^2) \]  
\[ \alpha_t = \alpha_{t-1} + \varepsilon_t^\alpha, \quad \varepsilon_t^\alpha \sim \mathcal{N}(0, \omega^2) \]  

where \( y_t \) is the log first differences of the metal price, \( \varepsilon_t^y, \varepsilon_t^h \) and \( \varepsilon_t^\alpha \) are mutually and serially uncorrelated disturbances. The log volatility \( h_t \) follows a stationary ARX(1) process with \( \phi < 1 \). In the model given in Equations (1)-(3), \( \exp(h_t) \) is the conditional variance of the transitory component \( \varepsilon_t^y \) of \( y_t \), therefore, we can interpret \( \alpha_t \) as the impact of the transitory metal price volatility on the level of the metal price. The parameter \( \beta \) measures the impact of metal price on its volatility. In the empirical section, the model in Equations (1)-(3) is estimated using the efficient Markov chain Monte Carlo (MCMC) sampler developed in Chan (2017).\(^1\) Our specification differ from Chan (2017) by constant mean specification \( \tau \) in Equation (1).

\(^1\) See Chan (2017, p. 27) for the priors used in the estimation.
The process \( \{h_t\}_{t=1}^T \) defined in Equation (2) defines the log conditional variance and unobserved and, thus, it is a latent process with initial state \( h_0 \) distributed according to a stationary autoregressive process of order 1, AR(1). The latent process \( \{h_t\} \) arises as an approximation to stochastic volatility diffusion of Hull and White (1987) and Chesney and Scott (1986) and, therefore, based on a well-developed theory. This latent process defined in Equation (2) is also more consistent with the unobserved volatility. Volatility is the result of flow of news into the markets and not directly observable. Thus, interpreting the latent volatility process \( \{h_t\} \) as representing the random and uneven flow of new information is convenient, because it is very difficult, if not impossible, to model the information flow directly. This interpretation of the stochastic volatility model is proposed by Clark (1973) and Tauchen and Pitts (1983), which is more realistic than the observable conditional variance of the GARCH models as a measure of volatility. As shown by Taylor (1986, 1994), the SV models can be seen analogous of continues time option pricing models and, therefore, fit naturally well into the theoretical framework most of the finance theory has been developed.

The SV model has some features that makes them more attractive in modeling volatility dynamics compared to other models such the GARCH. The conditional volatility in GARCH models is perfectly and deterministically explained by the past observations, whereas the SV model allows additional uncertainty in the volatility by introducing stochastic shock term \( \varepsilon_t^h \) in Equation (2). An important consequence of this feature of the SV models is the absence of any moment restriction requirements (see e.g. Meddahi and Renault 2004), which is an important requirement in the GARCH models and reduces their flexibility. The absence of moment restrictions in the SV models implies that they can have better in sample fit than the GARCH models and likely to give better forecasts unlike the GARCH models which are known with their poor out of sample forecasting performance (Danielsson 1994; Kim, Shephard and Chib 1998). Although they look simple in their dynamic property with an AR(1) specifications, the SV models indeed are quite flexible in their capacity to model persistence in volatility. Granger and Newbold (1976) show that autocorrelations of the log volatility process \( \{h_t\} \) implies an autoregressive moving average process for the square of \( y_t \) with orders (1,1), i.e. ARMA(1,1), and therefore can capture high persistence. Therefore, the AR(1) structure in Equation (1), when all components of the model is considered, is not
restrictive in terms of volatility persistence and, indeed, more flexible than a GARCH(1,1) process (Davidian and Carroll 1987; Shephard 1996).

3. Empirical Analysis

The data used in this study consisting of monthly US dollar closing prices of precious (Gold, Silver, Copper, Platinum, Palladium and Palladium) metals traded on the London Precious Metals Market. The data are taken from Datastream. We use the monthly frequency to characterize a dependence structure of the data. Researchers such as Reboredo (2013) noted that the drifts and noise could mask the dependence relationship between the series when high frequency data is used. Also, these complicate modeling of the marginal distributions through non-stationary variances, long-memory or sudden jumps. Thus, the drifts and noise may affect the daily or high-frequency data. The results of the study, that investigates the dependence relationship and others, may be insensitive to the choice of a daily or weekly frequency. Moreover, if there is highly volatility in the precious metal market, it may be difficult to capture linkage between precious metal price and its volatility on a daily or weekly basis. Hence, we prefer to use the monthly frequency data rather than high frequency (such as the daily or weekly frequency) data (see, Reboredo 2013, for a discussion). Before investigating the dynamic linkages between precious metal price and its volatility, we first apply the Augmented Dickey-Fuller (henceforth ADF) of Said and Dickey (1984) and the Phillip-Perron of Phillip and Perron (1988) (henceforth PP) unit root test to the precious metal price series to determine whether they are stationary or not. The tests are conducted for the levels of the series as well as for the first differenced series. The results from unit root tests for the each series indicate that the nonstationary null hypothesis cannot be rejected for the levels of the all precious metal price series while the nonstationarity null hypothesis can be rejected for the first differenced of the all series. This confirms that the each precious metals price return series are stationary². Thus, we use the precious metal price returns series calculated as the monthly percentage differences of the natural log of the precious metals price series. Thus, we use the data calculated as the log-returns \( r_t = 100 \times \ln(p_t/p_{t-1}) \), where \( p_t \) is the price at time \( t \). The log-returns data are plotted in Figure 1. The descriptive statistics for precious metals returns included in the sample along with the beginning date are given in Table 1. The sample period is not the same for each series. The data span is from the date reported in the first row of Table 1 to April 2017.

² Complete details of the unit root tests are available upon request from the authors.
We report the descriptive statistics for the monthly precious metals price return series in percent in Table 1. The descriptive statistics given in Table 1 are the mean, the standard deviation (S.D.), minimum (min), maximum (max), skewness, and kurtosis statistics, in addition to the Jarque-Bera normality test (JB), the Ljung-Box first [Q(1)] and the fourth [Q(4)] autocorrelation tests, and the first [ARCH(1)] and the fourth [ARCH(4)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroskedasticity (ARCH). $n$ indicates the number of observations for each precious metals price return series considered.
Table 1. Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Gold</th>
<th>Silver</th>
<th>Copper</th>
<th>Platinum</th>
<th>Palladium</th>
</tr>
</thead>
<tbody>
<tr>
<td>n</td>
<td>591</td>
<td>591</td>
<td>591</td>
<td>495</td>
<td>362</td>
</tr>
<tr>
<td>Mean</td>
<td>0.605</td>
<td>0.355</td>
<td>0.248</td>
<td>0.379</td>
<td>0.514</td>
</tr>
<tr>
<td>S.D.</td>
<td>5.896</td>
<td>9.603</td>
<td>7.560</td>
<td>7.695</td>
<td>9.541</td>
</tr>
<tr>
<td>Max</td>
<td>36.554</td>
<td>62.120</td>
<td>27.420</td>
<td>32.712</td>
<td>34.393</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.803</td>
<td>-0.533</td>
<td>-0.449</td>
<td>-0.271</td>
<td>-0.411</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>5.581</td>
<td>12.420</td>
<td>3.562</td>
<td>3.129</td>
<td>3.278</td>
</tr>
<tr>
<td>JB</td>
<td>838.886 ***</td>
<td>5076.840 ***</td>
<td>285.237 ***</td>
<td>487.316 ***</td>
<td>81.270 ***</td>
</tr>
<tr>
<td>Q(1)</td>
<td>1.940</td>
<td>0.077</td>
<td>17.379 ***</td>
<td>0.104</td>
<td>0.046</td>
</tr>
<tr>
<td>Q(4)</td>
<td>3.129</td>
<td>1.114</td>
<td>17.610 ***</td>
<td>1.159</td>
<td>3.287</td>
</tr>
<tr>
<td>ARCH(1)</td>
<td>13.048 ***</td>
<td>1.262</td>
<td>36.962 ***</td>
<td>16.342 ***</td>
<td>18.046 ***</td>
</tr>
<tr>
<td>ARCH(4)</td>
<td>107.554 ***</td>
<td>121.567 ***</td>
<td>52.084 ***</td>
<td>55.492 ***</td>
<td>23.859 ***</td>
</tr>
</tbody>
</table>

Note: Table reports the descriptive statistics for the monthly percentage change in price series. n donates the number of observations for each series. In addition to the mean, the standard deviation (S.D.), minimum (min), maximum (max), skewness, and excess kurtosis statistics, the table reports the Jarque-Bera normality test (JB), the Ljung-Box first [Q(1)] and the fourth [Q(4)] autocorrelation tests, and the first [ARCH(1)] and the fourth [ARCH(4)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroskedasticity (ARCH). *** represents significance at the 1%, level.

The mean of gold, silver, copper, platinum, palladium and palladium price returns are about 0.6, 0.36, 0.25, 0.38 and 0.51, respectively. This shows that it is lowest for the copper price return and is biggest for gold return. Second, it is found on examining the S.D values for these precious metals price return series that the volatility of silver, platinum and palladium prices was higher than the volatility of gold prices. This situation shows that there is higher volatility on the precious metals market of silver, copper, platinum, palladium and palladium than on the market of gold. It may be said that there is the probability of great falls in gains on the market of silver, copper, platinum, palladium and palladium depending on the negative values of skewness except of gold markets where skewness is positive. It was found that the kurtosis statistics of precious metals price return series each had a fat-tailed distribution. A close examination of Jarque-Bera statistics in addition to skewness and excess kurtosis statistics indicates that all these series are skewed to the left with fat tails. This results shows that the series have non-normal distribution. Moreover, we also calculate Ljung–Box Q statistics and ARCH-LM statistics at 1 and 4 lags for the squares of the all return series. Ljung-Box statistic indicate that there is a significant serial correlation for copper market return; while significant serial correlation is not found for gold, silver, platinum, palladium and palladium markets returns. There are ARCH (autoregressive conditional heteroscedasticity) effects in all the return series as suggested by ARCH-LM statistic.
There is widespread concern that large fluctuations in the price of gold, silver, copper, platinum, palladium and palladium are harmful especially to the economies of oil exporters and importers. In addition to that, volatility in the price of gold, silver, platinum, palladium and palladium also pose difficulties for policy makers. Figure 1 shows that there have been large and persistent fluctuations in the metal prices which must have put stress on the global economy since the suspension of dollar’s convertibility into gold in the August and November of 1971. The United States left American Dollar to fluctuation when the USA announced on August 15th 1971 that it had retreated from Bretton Woods Agreement. Following this, England left Pound to fluctuation. States which had put their monetary unit on American Dollar and thus on gold with Bretton Woods also pursued similar ways. Developing countries, beginning with the USA, increased their gold reserves and issued money. The US Dollar and the monetary units of developed countries began to depreciate. Depreciation of the money of those developed countries, the main customers of OPEC countries, resulted in reduction in OPEC countries’ income. Thus, gold price, which had been fixed as 25 ounces/a Dollar for years with OPEC countries’ decision to index oil price to the price of gold, tended to rise. Stagflation-based crisis occurred when inflationist pressure stemming from oil prices was added to the recession in the US. After Egypt and Syria declared the Yom Kippur War against Israel in October 1973, the Arabic members of OPEC imposed an embargo on oil export. Those countries decreasing oil supply caused a rise in oil prices when the demand for oil remained constant. Due to OPEC’s reduction in oil supply, inflation and stagflation; gold price rose until 1980. This movement beginning with 35 ounces/a Dollar ratio especially reached the level of 850 ounces/a Dollar with Hunt Brothers’ Silver Speculation in 1979. After that, in the period between early 1980s and early 2000s the prices were set at a certain interval. Therefore, volatility in prices in this period can be said to be small and to be at a certain interval. The upward trend in gold, silver, copper, platinum and palladium prices observed since the early 2000s came to an end in 2012. Following this date and including 2014, falls occurred in the price of precious metals. One of the causes for decrease in precious metal prices in 2014 was that investors did not consider precious metals as “safe haven”, another cause was that the return of those metals was relatively lower than that of other instruments of investment, and still another was that China and India—the greatest consumers of gold in the world—had reduced demands for gold. Another reason was that FED had increased interest rates due to improving economic conditions and that it had signaled that it would continue raising interest rates and this caused a downward pressure on prices. Partial increases were observed in the period following 2014. In other words, it may be said based on
Figure 1 that gold, silver, copper, platinum, palladium and palladium prices also have large and persistent fluctuations and that those fluctuations cause stress in global economy. Great increases occurred in precious metal price returns especially in the mid 1980s, in 1990/91, after 1999, between 2003 and late 2008, in 2009/10, and in the period following 2015. It is evident that major sustained precious metals price returns declines occurred other substantially sub-periods.

To investigate the dynamic nexus between precious metal price returns and its volatility, we first estimate the time-varying parameter stochastic volatility in mean (TVP-SVM) model for gold, silver, copper, platinum, palladium and palladium price return series. In order to estimate the parameters and 90% confidence intervals 50,000 posterior draws with a burn-in period of 50,000 is used. The estimation results of the posterior moments and quantiles of the model parameters reported in Table 2. The estimation results obtained for each series indicate that there are significant similarities between the estimates which are associated with the parameters in the stochastic volatility AR(1) process of $h_t$ and the estimates obtained for all series. For instance, the transition of $h_t$ has been found to be highly persistent with the posterior mean of $\phi$ which is estimated to be about 0.94 to 0.97 with a 90% credible interval (0.928, 0.995). Moreover, we also note that $\beta$, the coefficient which is associated with the lagged gold, silver, copper, platinum, palladium and palladium price return, is estimated to be positive and significate at the nominal 10% significance level. Its 90% credible confidence interval does not include 0. This indicates that lagged gold, silver, copper, platinum, palladium and palladium price return series has a positive impact on current log-volatility of their return series.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Posterior mean</th>
<th>Standard error</th>
<th>90% credible interval</th>
<th>Parameter</th>
<th>Posterior mean</th>
<th>Standard error</th>
<th>90% credible interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau$</td>
<td>0.508</td>
<td>0.258</td>
<td>(0.083, 0.933)</td>
<td>$\tau$</td>
<td>0.560</td>
<td>0.408</td>
<td>(-0.111, 1.232)</td>
</tr>
<tr>
<td>$\mu$</td>
<td>2.960</td>
<td>0.224</td>
<td>(2.622, 3.302)</td>
<td>$\mu$</td>
<td>3.989</td>
<td>0.142</td>
<td>(3.750, 4.224)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.025</td>
<td>0.004</td>
<td>(0.019, 0.031)</td>
<td>$\beta$</td>
<td>0.020</td>
<td>0.002</td>
<td>(0.016, 0.024)</td>
</tr>
<tr>
<td>$\phi$</td>
<td>0.966</td>
<td>0.010</td>
<td>(0.947, 0.981)</td>
<td>$\phi$</td>
<td>0.951</td>
<td>0.012</td>
<td>(0.928, 0.965)</td>
</tr>
<tr>
<td>$\sigma^2$</td>
<td>0.024</td>
<td>0.006</td>
<td>(0.016, 0.035)</td>
<td>$\sigma^2$</td>
<td>0.022</td>
<td>0.005</td>
<td>(0.015, 0.031)</td>
</tr>
<tr>
<td>$\omega^2_\phi$</td>
<td>0.004</td>
<td>0.001</td>
<td>(0.003, 0.006)</td>
<td>$\omega^2_\phi$</td>
<td>0.003</td>
<td>0.001</td>
<td>(0.002, 0.004)</td>
</tr>
<tr>
<td>$\omega^2_{\phi,\tau}$</td>
<td>-0.003</td>
<td>0.004</td>
<td>(-0.011, 0.003)</td>
<td>$\omega^2_{\phi,\tau}$</td>
<td>-0.001</td>
<td>0.003</td>
<td>(-0.006, 0.003)</td>
</tr>
<tr>
<td>$\omega^2_{\tau}$</td>
<td>0.111</td>
<td>0.056</td>
<td>(0.049, 0.224)</td>
<td>$\omega^2_{\tau}$</td>
<td>0.104</td>
<td>0.054</td>
<td>(0.047, 0.211)</td>
</tr>
</tbody>
</table>
\[
\begin{align*}
\tau &\quad 0.292 &\quad 0.337 &\quad (-0.263, 0.848) &\quad \tau &\quad 0.795 &\quad 0.370 &\quad (0.186, 1.404) \\
\mu &\quad 3.559 &\quad 0.157 &\quad (3.303, 3.804) &\quad \mu &\quad 3.565 &\quad 0.196 &\quad (3.257, 3.885) \\
\beta &\quad 0.019 &\quad 0.003 &\quad (0.015, 0.023) &\quad \beta &\quad 0.019 &\quad 0.003 &\quad (0.013, 0.025) \\
\phi &\quad 0.943 &\quad 0.015 &\quad (0.917, 0.965) &\quad \phi &\quad 0.956 &\quad 0.015 &\quad (0.929, 0.976) \\
\sigma^2 &\quad 0.029 &\quad 0.006 &\quad (0.020, 0.040) &\quad \sigma^2 &\quad 0.027 &\quad 0.007 &\quad (0.018, 0.040) \\
\omega_0^2 &\quad 0.004 &\quad 0.001 &\quad (0.003, 0.006) &\quad \omega_0^2 &\quad 0.004 &\quad 0.001 &\quad (0.002, 0.005) \\
\omega_{\tau}^2 &\quad -0.002 &\quad 0.004 &\quad (-0.008, 0.003) &\quad \omega_{\tau}^2 &\quad -0.002 &\quad 0.003 &\quad (-0.008, 0.003) \\
\omega_\tau^2 &\quad 0.098 &\quad 0.050 &\quad (0.046, 0.193) &\quad \omega_\tau^2 &\quad 0.103 &\quad 0.056 &\quad (0.045, 0.202)
\end{align*}
\]

Note: The results are based on 50,000 posterior with a burn-in period of 50,000.

The estimation results of the precious metal price return volatility \((h_t)\) and its time-varying impact \((\alpha_t)\) on precious metal price return as well as the associated 90% credible confidence intervals plotted in Figure 2. The left panel of the Figure 2 reports the estimates of \(h_t\). The estimates of \(h_t\) typically show high volatility. These estimates have similarities for all series. On examining the estimation results for gold, silver, copper and platinum, for instance, high volatility was observed in the period between early 1970s and the 1980s. The volatility decreased between early 1980s and mid-1990s. It increased again in the period between mid-1990s and early 2010s. After that year volatility decreased and it increased again following the year 2015. On analyzing all the dynamics of volatility through time, it is found that volatilities both in early 1970s and in early 1980s are quite high. The time-varying impact of the volatility of precious metal price return on its price return series are reported in right panel of the Figure 2. We also report the 90% confidence intervals represented in the shaded (in gray color) regions around the time-varying impact of precious metal price return volatility on its price return \((\alpha_t)\) lines. The results from estimation of \(\alpha_t\) for each series show that there is a substantial time-variation in the impact of uncertainty on precious metal price, highlighting the importance of the time-varying parameter extension in this study. An examination of \(\alpha_t\) estimation results concerning gold, silver, copper and platinum metal price series.
demonstrates that estimates are negative and significant with the exclusion of mid-1970s and early 1980s where estimates are approximately zero and insignificant. The results obtained for these two sub-periods show that the effects of volatility of gold, silver, copper and platinum metal price series on these precious metal price return series are not statistically significant in these periods. On the other hand, the estimation results for $\alpha_t$ are negative for all precious metal price return series excluding these two sub-periods. The estimation results are also statistically significant. It may be said that the negative effect was quite strong in the period between mid-1980s and mid-2000s. The evidence from estimation results reported in the right panel of Figure 2 indicate that the precious metal price return volatility has negative impact on its price return over the time with the exception of two small sub-periods.

Figure 2. Evolution of Volatility and Impact of Volatility on Growth

(a) Gold

(b) Silver

(c) Copper
Note: The figure plots the evolution of the price volatility $h_t$ (left panel) and time-varying impact of the price volatility on price growth $\alpha_t$ (right panel). The solid lines are the estimated posterior means and the shaded regions denote the 90% credible confidence intervals. The results are based on 50,000 posterior with a burn-in period of 50,000.

It is also clear from Figure 2 that there are correlations between the negative predictions of $\alpha_t$ and big positive volatility shocks. We observe from the estimation results given in left panel of Figure 2 that precious metal price volatility has large positive shocks in
periods corresponding to Suspension of dollar’s convertibility into gold in August – November 1971, The Smithsonian Agreement in December 1971 – January 1973, End of the Bretton Woods fixed exchange rate system in March 1973 onwards, IMF gold sales program in June 1976 – May 1980, Iranian hostage crisis in November 1979 – January 1981, Black Monday stock market crash in October 1987, Gulf War in August 1990 – February 1991, Asian crisis in 1997/2000, September 11th Terrorist Attack in September 2001, Iraq War in March – April 2003, and the Global Financial Crisis in 2008. The findings of the study by Gil-Alana et al. (2015) indicate that there are structural breaks in almost all precious metal prices considered in their study, with the exception of the palladium series. The results of this study show evidence of an increase in the degree of persistence across time in the majority of cases. The evidence of an increase in the degree of persistence across time in the majority of cases implies that shocks to these precious metals will be permanent. This requires strong policy measure restore the series into their equilibrium levels in the event of negative shocks. Recently, the study of Balcilar and Ozdemir (2017) show that the impact of uncertainty of commodity prices return on commodity prices return series negative during these large positive shock periods. This evidence indicates that commodity price hikes in these periods are reversed. This state of affairs can be interpreted as the sign of the start of a declining trend in precious metal prices following the price hikes. The crashes have been found in the empirical study on financial markets cause large volatility shocks, which is a similar behavior in stock markets.

We find substantial time variation in the effect of the uncertainty on precious metal prices which needs to be closely considered. There are several structural breaks in the coefficient measuring the effect of the uncertainty. They all have negative signs. We observe important demand shifts in the precious metals causing price shocks since the 1970s. This is emphasized by several researchers. Researchers such as Kilian (2010) and Baumeister and Kilian (2016a,b) noted that shocks to the flow supply of precious metal did not influence its price since 1971. The major changes in the price of precious metal during 1971-1973, 1976-1981, and 2000-2008 have been due to the demand shocks triggered by global business cycles. In addition, the forward looking behavior by traders and the resulting speculative demand have been a cause of price fluctuations. Episodes such as the Asian crisis in 1997/2000, September 11th Terrorist Attack in September 2001, Iraq War in March – April 2003, and the Global Financial Crisis in 2008 have all generated speculative demand shocks which can cause significant and instant impact on the price of precious metal (see Kilian
2010; and Baumeister and Kilian 2016a,b, for a discussion). Under these demand driven dynamics in the market for precious metals, uncertainty about their future prices may result in chances in their price. The speculative demand shocks can be generated by expectations. The news related to the precious metals demand or supply may lead to jumps in their prices. In order to see this consider the following events as elaborated by Kilian (2010) and Baumeister and Kilian (2016a,b). The precious metal inventories in the current period will increase ceteris paribus if expected future supply declines or expected future demand increases. The result will be an immediate shift in the current demand curve along the supply curve leading to increase in the price of precious metal.

The elements determining the price of precious metal–excluding supply and demand conditions–are the use of precious metals as an instrument of investment, considering precious metals–mainly gold–as a safe haven in periods of crisis, and changes in the reserves of central banks. Serious increases were observed in precious metal prices and in their volatility volatility especially following the Asian crisis in 1997/2000, September 11th Terrorist Attack in September 2001, Iraq War in March – April 2003, and the Global Financial Crisis in 2008. One of the main causes for the increase in the price of precious metals in those periods may undoubtedly be said to be the fact that precious metal–mainly gold–was preferred as the “safe haven”. The reasons for the fall in the price of precious metals in 2014 included the fact that investors had not considered precious metals as a “safe haven” as much as they used to do, that precious metals returns were relatively lower than the returns of other instruments of investment and that China and India–the greatest consumers of gold in the world–had reduced demands for gold. Another reason was that FED had increased interest rates due to improving economic conditions and that it had signaled that it would continue raising interest rates and this caused a downward pressure on prices. Besides, it may also be argued that the price of precious metals went down due to institutional investors’ reduced interest in precious metals which had been seen as the “safe haven” before, due to weakening in China and India’s physical demands, and due to expectations that FED would raise interest rates. The substantial time variation in the impact of the uncertainty on precious metal prices constitutes one of the most important findings of our study. As a matter of fact, the coefficient used to measure the effect of the uncertainty has several significant structural breaks with a negative sign. Therefore, there is a big necessity to examine the variation closely.
4. Conclusion

The price of precious metals, one of key global macroeconomic variables, are continuously monitored by almost all firms, investors, governments, policy makers and managers. Expectations in relation to precious metal prices are an important element for actors of economy to make decisions. Uncertainty is the main variable in decisions about the future. Because the majority of economic decisions depending on future expectations contain precious metal prices, uncertainties in precious metal prices play very important roles in helping actors of economy to make decisions. Therefore, this study analyzes the dynamic relationships between the price of precious metals such as gold, silver, copper, platinum, palladium and palladium and the volatility series of them.

As is pointed out in Meddahi and Renault (2004), while GARCH models impose restrictions on conditional moments in a standard GARCH type model, SV models do not impose restrictions on conditional moments. To our knowledge, all studies available in the literature concerning precious metal prices and the variables of precious metal prices have used GARCH type models in which volatility is determined deterministically. Uncertainty or volatility is not determined stochastically in those GARCH type models used. In this study, we have used stochastic volatility model for modelling precious metal price return volatility by allowing stochastic volatility shocks. Besides, we have also specified the effects of structural breaks occurring in the price of precious metals with time-varying parameters. Thus, this study contribute to the existing literature with allowing time-varying impact of uncertainty of precious metal price changes return on the precious metal prices where the uncertainty is modelled with a stochastic volatility model that allows volatility shocks.

One of the important results obtained in this study is that it captures the historically experienced developments in relation to precious metal market volatility dynamics. Another finding of this study is that the impact of precious metal price return uncertainty series on the precious metal price series show substantial time variation. This time-varying impact is significantly negative. The effect of price uncertainty have breaks in some periods in the time-sharp breaks were observed in four periods in the coefficient where precious metal price return volatility series had effects on precious metal return series. These periods correspond to the historical events of the invasion of Kuwait in 1990/91, the Asian crisis in 1997/2000, September 11th Terrorist Attack in September 2001, Iraq War in March – April
2003, and the Global Financial Crisis in 2008 periods. Another important finding of this study was that the variability of dynamic links between precious metal price return series and its uncertainty series had time-varying nature. Stochastic volatility model prediction results for price return series for the precious metals of gold, silver, copper, platinum and palladium show that volatility shocks play important roles in these series. In addition to that, another finding was that precious metal price volatility had remarkable persistency. Actually, decreasing precious metal prices and effects of uncertainty of metal price return series on the metal price return series becomes insignificant or even negative may cause large positive volatility shocks and extremely high volatility periods. Prospective researchers are recommended to investigate whether or not the time-varying parameter variants of the stochastic volatility model also fit other macroeconomic or financial time series better than the other models used in the literature.
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