JEL Classification: C22; G14; C58; L61
Keywords: precious metals; Russia; long memory; structural breaks; volatility spillover, DCC-MGARCH

Volatility Dynamics of Precious Metals: Evidence from Russia

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Abstract
This paper examines the volatility dynamics of four precious metals (gold, silver, platinum, and palladium) that are traded in Russia from 2000 to 2014. More specifically, it focuses on the following issues: (i) Presence of long memory property and structural breaks in returns and volatility series of precious metals by deploying semi-parametric methods and modified ICSS algorithm; and (ii) Correlation levels among precious metals by using DCC-MGARCH approach. The findings show that there is strong evidence of long memory property in the conditional volatility of all precious metals. Concerning the dynamic constant correlation, precious metals are highly correlated with each other. Although gold is the least volatile metal, the correlation increases significantly when it is paired with other precious metals. The findings further suggest that silver can be a good diversifier investment due to its low correlation with other precious metals.

1. Introduction

Over the last three decades, the financial markets were shaped by severe financial crises. While the 1990s witnessed local and regional financial crises including Asian, Mexican, Brazilian and Russian financial crises, the world economy was hit by the global financial crisis during the 2000s. This was the moment it became clear that there was a threat of contagion of the global financial crisis due to the increased linkages among the financial markets. In particular, stock markets suffered steep losses and investors lost confidence in the financial markets. The panic of high volatility and contagion effect in the financial markets has led investors to consider alternative instruments to hedge increasing risk in their portfolios. At this point, precious metals have emerged as a safe haven and their low correlation with other assets increased their attractiveness for investors.

While the global financial crisis increased the precious metals' appeal, few years later, the European sovereign debt crisis added even more weight to the risk diversifier notion of precious metals. Meanwhile, a significant number of countries across the world started purchasing large holdings of the precious metals, namely gold, in order to combat the economic downturn. Among these countries, China and Russia, in particular, emerged as the largest gold buyers in the aftermath of the global financial crisis. When it comes to precious metals, Russia already has a solid reputation as the largest palladium, the 2nd largest platinum, the 4th largest gold, and the 5th largest silver producer in the world (Blanchard, 2014). However, in recent years, Russia has received further attention due to its aggressive gold purchase, which contributed to the increasing global volatility in the price of precious metals (World Gold Council, 2015).

Despite the position of Russia in the world precious metal market, none of the studies in the previous literature have considered to investigate the volatility of precious metals in Russia. As precious metals are used for investment and as well as for industrial applications in electronics, automotive and dentistry, the predictable variations in the precious metals' price changes is important for risk management strategies. In this context, this paper is a first attempt to address this gap in the literature by examining the volatility dynamics of precious metals in Russia.

The main purpose of this study is to examine the volatility dynamics of four precious metals including gold, silver, platinum and palladium that are traded in Russia from 21 April 2000 through 21 November 2014. To be more specific, in the first part of our study, we examine the long memory property and structural break in returns and volatility of four precious metals in Russia. The importance of long memory property stems from its link with Efficient Market Hypothesis (EMH). The presence of long-memory property provides evidence against weak-form market efficiency and the predictability of the price return increases in the presence of long memory. To test long memory property, we use the GPH estimation of Geweke and Potter-Hudak (1983) in conjunction with the modified GPH developed by Smith (2005). While studying long memory, it is also important to detect structural breaks which can mimic long memory behavior and lead to seriously biased estimates and volatility. We further apply a modified ICSS algorithm to detect the structural breaks in the precious metals series and run the tests of both Shimotsu *(*2006*)* and Qu (2011) to investigate whether the observed long memory behavior is true or spurious. In the second part, we examine the volatility spillover among the four precious metals. Motivated by the recent financial crisis, we split the sampling period into two parts to check the volatility spillover among the precious metals during the pre-crisis (2000-2006) and post-crisis periods (2007-2014). In order to achieve this task, we calculate the correlations obtained from the DCC–MGARCH model of Engle (2002). This model is time-variant and it enables us to have the flexibility of univariate GARCH with two-step estimation. Hence, we can see the changes in the conditional correlations of precious metals before and after the recent financial crisis.

Our empirical results suggest no evidence of long memory in the return series of gold, silver and platinum. However, palladium returns exhibit long memory property. Given the fact that Russia dominates the palladium market and has significant impact on supply and price of palladium (Bouchentauf, 2011), this result should be carefully interpreted by the policy makers and as well as by the investors. Meanwhile, the results for the squared returns (proxy for volatility) provide different results from those for the return series, indicating that long memory property exists in the volatility of all four precious metals. Our findings further present evidence of structural breaks in almost all cases except palladium. The robustness tests confirm that long memory property cannot be explained by structural breaks, suggesting that volatility series are true of long memory processes. Moreover, our findings document that there are significant volatility spillovers across the precious metal returns. It is important to note that dynamic correlations among precious metals increased significantly in the post-crisis period in comparison with pre-crisis period. Nevertheless, while the strongest correlation occurs between the palladium–platinum, either weak or no dynamic conditional correlation is found for each pair of precious metal returns when silver is involved.

The remainder of this paper proceeds as follows. Section 2 provides information on the data and methodology. Section 3 discusses empirical findings and Section 4 concludes.

2. Literature Review

While a substantial literature exists on the analysis of volatility of stock and foreign exchange markets, less attention is given to volatility dynamics of precious metals. In recent years, the popularity of precious metals has increased due to their roles as a safe haven during times of economic turmoil (Baur and McDermott, 2010; Baur and Lucey, 2010; Reboredo, 2013). The recent global financial crisis along with the growing interest towards precious metals have also encouraged further empirical research in this area, and stimulated the growth of studies that focused on the long memory of precious metals (Canarella and Pollard, 2008; Batten et al, 2010; Cochran et al, 2012; Ewing and Malik, 2013; Soytas et al., 2009; Kirkulak and Lkhamazhapov, 2014; Gil-Alana and Tripthy, 2014). Among other points, these studies converge in their findings, which suggest that there is a long memory in precious metal market.

While understanding the presence of long memory is worth considering for risk management and portfolio diversification, some studies questioned whether structural breaks may cause spurious long memory. Arouri et al (2012) examined long memory properties and structural breaks in returns and volatility of the four precious metals including gold, silver, platinum and palladium, which are traded on the COMEX. They found strong evidence of long memory in the conditional return and volatility of precious metals, even after potential structural breaks are controlled for. A study of Gil-Alana et al. (2015) similarly tested the persistence of five metal prices (gold, silver, platinum, palladium, and rhodium) based on a fractional integration modeling framework while identifying structural breaks. They found evidence of long memory behavior and structural breaks in almost all cases except palladium.

Another strand of literature examines the volatility spillover of precious metals. Previous studies have considerably contributed to the volatility spillover for particularly four major precious metals amongst others. Morales (2008), for instance, examined the volatility spillovers between gold, silver, platinum and palladium returns from 1995 to 2007. Their findings show that there is evidence of volatility spillovers running in a bidirectional way in all cases of precious metals, with the exception of gold. Interestingly, while gold affects other precious metals, there is little evidence in the case of the other precious metals influencing the gold market. Using multivariate GARCH models, Hammoudeh et al. (2010) examined conditional volatility and correlation interdependence among four major precious metals. Their results show that all the precious metals are moderately sensitive to their own news and are weakly responsive to news spilled over from other metals in the short run. Among four precious metals, platinum and palladium have the highest conditional correlations among any pairs of the precious metals followed by gold and silver. Sensoy (2013) attempted to detect the volatility shifts in the returns of gold, silver, platinum and palladium from 1999 to 2013. The results suggest that gold has a volatility shift contagion effect on all precious metals, however other metals have no such effect on gold. This can be explained by the functions of gold as a store of value and a medium of exchange.

Previous studies further investigated the volatility spillover between precious metals and other commodities in order to build hedging strategies involving precious metals. Hammoudeh and Yuan (2008) examined volatility behavior of gold, silver and copper in presence of oil, and interest rate shocks. Using daily prices and GARCH-based models, they state that oil volatility together with rising interest rates may dampen and negatively affect metals' volatilities. In another study, Sari et al. (2010) examined the co-movements and information transmission between the spot prices of four precious metals and oil prices. They found strong evidence of significant transmission of volatility and dependence between gold and oil returns. Mensi et al. (2015) examined the time-varying linkages of WTI oil, gold, silver, wheat, corn and rice in Saudi Arabia. They employed bivariate DCC-FIAPARCH model and found strong evidence of time-varying conditional correlations between the silver commodity futures and the stock markets in Saudi Arabia. In a more recent paper, using a wavelet approach, Barunik et al. (2016) investigated dynamic correlations between the pairs of gold, oil and stocks between 1987 and 2012. Their findings suggest that the correlations among gold, oil and stocks were relatively lower during the pre-global financial crisis. However, the correlations dramatically increased following the global financial crisis, suggesting decrease in portfolio diversification benefits.

Other recent studies have investigated volatility spillover between precious metals and other financial assets, including stocks and foreign exchanges. Arouri et al (2014) examined the volatility spillovers between gold prices and stock market in China from 2004 to 2011.Their results show significant return and volatility cross effects between gold prices and stock prices. In particular, past gold shocks play a crucial role in explaining the time-varying patterns of conditional volatility of Chinese stock returns. Antonakakis and Kizys (2015) studied the dynamic spillovers between five commodities (gold, silver, platinum, palladium, and oil) and four exchange rates (EUR/USD, JPY/USD, GBP/USD and CHF/USD) from 1987 through 2014. Their findings show that gold, silver and platinum (CHF/USD and GBP/USD) are net transmitters of returns and volatility spillovers, whereas palladium and crude oil (EUR/USD and JPY/USD) are net receivers. Balcilar et al. (2015) used the Bayesian Markov-switching vector error correction model and the regime dependent impulse response functions to examine the transmission dynamics between oil, precious metals (gold, silver, platinum, and palladium) and the US dollar/euro exchange rate. Their results indicate that gold and silver have the highest historical correlation followed by oil and platinum. In addition, their results suggest that gold prices have the most significant impact on silver prices, while the impact of those changes is the lowest for oil. This effect can be attributed to the fact that gold and silver share similar features as monetary and investment assets.

3. Data and Methodology

We use daily closing prices for four precious metals (gold, silver, platinum and palladium). The sampling period covers the period from 21 April 2000 through 21 November 2014. The number of total observations is 3632. In Russia, the central bank is the only source, where the comprehensive data set regarding the four precious metals can be taken. In 2013, Moscow Exchange started precious metals trading by introducing spot gold and silver trading. However, there has been yet no platinum and palladium spot trading transactions at Moscow Exchange. Therefore, we used the data from the Central Bank of Russia.

The Russian Central Bank together with Gokhran plays a crucial role in the precious metal market. Gokhran is the state repository under the Russian Ministry of Finance and it is in the charge of buying, storing and selling various precious metals and gems in Russia. While the Russian Central Bank dominates the gold market, Gokhran plays a crucial role for the rest of the precious metals. The total precious metal reserves of Gokhran are a state secret and independent from those of the Russian Central Bank. Aside from the Russian Central Bank and Gokhran, the commercial banks take active roles in the precious metal market. In order to trade the precious markets, commercial banks need a license from the Russian Central Bank. Industrial users and investors are required to purchase precious metals from these licensed commercial banks. Indeed, commercial banks act as financial intermediaries among mining companies, the Russian Central Bank, and the Gokhran. Commercial banks finance the mining companies through purchasing the precious metals and then sell them either to the Gokhran or to the central bank. The Russian Central Bank sets the precious metal prices every day. The precious metals prices are based on London spot metal market and then converted into ruble using the weighted average rate of the Moscow Interbank Currency Exchange. All the precious metal prices are in ruble. (International Metallurgical Research Group, 2014).

3.1 Long Memory

The long memory properties in return and volatility of precious metals are estimated by using the Geweke and Porter-Hudak (1983) (henceforth GPH). This method is a semi-parametric procedure of the long memory parameter d which can capture the slope of the sample spectral density through a simple OLS regression based on the periodogram, as follows:

$$\log\left[I(w_j)\right] = \beta_0 + \beta_1 \log\left[4\sin^2\left(\frac{w_j}{2}\right)\right] + \varepsilon_j \tag{1}$$

where $w_j = 2\pi j/T,\ j = 1, 2, ..., m$ (the band-width parameter) and ε_j is the residual term. The sample periodogram, $I(w_j) = \frac{1}{2\pi T}\left|\sum_{t=1}^{T} r_t e^{-w_j t}\right|^2$, is the Fourier frequency at $m = \sqrt{T}$. Where r_t is covariance stationary time series and the estimate of $\hat{d}_{GPH}$ is $-\hat{\beta}_1$. The long memory effect is high where 0 < d < 1.

Smith (2005) pointed out that the GPH estimator is biased due to the impact of level shifts in volatility. He proposed a modified GPH (mGPH) estimator that minimizes this bias by including additional regressors in the estimation equation. The mGPH includes supplementary regressor $-\log(p^2 + w_j^2)$ in the log-periodogram regression where p is estimated as $p = kj/n$ for some constant $k > 0$. Here, j denotes the number of the periodograms in d estimation. Smith (2005) used different values for k and suggested that the modified GPH estimates perform well when $k = 3$.

3.2 Modified Iterated Cumulative Sum of Squares (ICSS)

In order to detect structural breaks, we use modified Iterated Cumulative Sum of Squares (ICSS) algorithm which is corrected for conditional heteroscedasticity. The modified ICC was originally introduced by Inclan and Tiao (1994) and later developed by Sansó, et al. (2004). The ICSS test can produce spurious changes in the unconditional variance, when the series are leptokurtic and conditionally heteroskedastic. To overcome this problem, Sansó, et al. (2004) proposed a non-parametric adjustment based on the Bartlett kernel. The null hypothesis of a constant unconditional variance is tested against the alternative hypothesis of a break in the unconditional variance. The Modified Inclán and Tiao (1994) statistic is given as:

$$Modified\ \ ICSS = \max_k \left|(T/2)^{0.5} G_k\right|, \tag{2}$$

where $G_k = (\hat{\gamma}/2)^{0.5}\left[C_k - \left(k/T\right)C_T\right]$ and $C_k = \sum_{t=1}^{k} r_t^2 \ \ for\ k = 1,...,T$

with T being the total number of observations, r_t denotes gold return series. $\hat{\gamma} = \hat{\delta}_0 + 2\sum_{i=1}^{m}\left[1 - i(m+1)^{-1}\right]\hat{\delta}_i$, $\hat{\delta}_i = T^{-1}\sum_{t=1}^{k}\left(r_t^2 - \hat{\sigma}^2\right)\left(r_{t-1}^2 - \hat{\sigma}^2\right)$ and $\hat{\sigma}^2 = T^{-1}C_T$. m refers to a lag truncation parameter used in the procedure in Newey and West (1994). The modified ICSS statistic $\max_k \left|(T/2)^{0.5} G_k\right|$ shows the same asymptotic distribution as that of $\max_k \left|(T/2)^{0.5} D_k\right|$ and simulations generate finite-sample critical values.

3.3 Shimotsu's Approach

There are two tests proposed by Shimotsu (2006) to distinguish between long memory and structural breaks. One of the tests is sample splitting and the other test is *díth* differencing. The first test estimates the long memory parameter over the full sample and over different sub-samples. Let b be an integer which splits the whole sample in b sub-samples, so that each sub-sample has *T/b* observations. The main concern of sample splitting is to examine whether the estimate of the full-sample d parameter is equal to the d parameter of each sub-sample. Define $\hat{d}$ $(1,2,3, \dots b)$ be the local Whittle estimator of the true long memory parameter d_0 computed from the *ith* sub-sample, we then compute the following expressions:

$$\hat{d}_b = \begin{pmatrix} \hat{d} - d_0 \\ \hat{d}^{(1)} - d_0 \\ \vdots \\ \hat{d}^{(b)} - d_0 \end{pmatrix}, A = \begin{pmatrix} 1 & -1 \cdots & 0 \\ \vdots & \vdots \ \cdots & \vdots \\ 1 & 0 \ \cdots & -1 \end{pmatrix} \tag{3}$$

We test the null hypothesis $H_o = d_0 = d_0^{(1)} = d_0^{(2)} \ldots d_0^{(b)}$ against structural break where $\hat{d}_0 = 1,2,3, \ldots b$ is the true long memory parameter of d from the *i*th subsample using the Wald statistic given below:

$$W = 4m \left(\frac{c_{m/b}}{m/b}\right) A\hat{d}_b (A\Omega A')^{-1} \left(A\hat{d}_b\right)',$$
$$c_m = \sum_{j=1}^{m} v_j^2 \; ; \; v_j = logj - \frac{1}{m}\sum_{j=1}^{m} logj \tag{4}$$

The Wald statistic follows a Chi-squared limiting distribution with b − 1 degrees of freedom. m is some integer representing the number of periodogram ordinates of $m < T$. Shimotsu (2006) states that the larger values of m do not necessarily increase the explanatory power, therefore we set two values for b: b=2 and b=4.

Shimotsu (2006) proposes dth differencing test that identifies the accuracy of the long memory parameter estimate. The differenced series is tested for stationarity using the PP test (Phillips-Perron, 1988) and the KPSS test (Kwiatkowskinet al., 1992). Assuming that Y_t follows a truncated I (*d*) process with initialization at t=0:

$$Y_t - \mu = (1 - L)^{-d} u_t I_{t\geq 1} \tag{5}$$

where μ is the mean Y_t when d<1/2, we have $T^{-1}\sum_{t=1}^{T} Y_t - \mu = \mathrm{O_P}(T^{d-1/2})$ and as discussed in Shimotsu (2006) $(1 - L)^{-d}(Y_t - T^{-1}\sum_{t=1}^{T} Y_t) = u_t + \mathrm{O_P}(T^{d-1/2} t^{-d})$. If $d \geq 1$, the second term on the right has a significant effect on the sample statistics of the d^{th} differenced demeaned data. Under the assumptions presented in Shimotsu (2006), the two statistics, Z_t and η_u , converge towards $P(W(r, d_o))$ and $K\big(W(r, d_0)\big)$ as $T \to \infty$ where $W(r, d) = W(r) - w(d)\big(\Gamma(2 - d)\Gamma(d + 1)\big)^{-1} r^{1-d} W_{d+1}(1)$.

3.4 Qu's Approach

Qu (2011) uses the properties of local Whittle estimator of *d*, say $\hat{d}_w$, obtained by minimising the concentrated Whittle likelihood function.

$R(d) = LogG(d) - 2m^{-1}\, d \sum_{j=1}^{m} log\lambda_j$ with respect to d to test whether the series has long memory or a break.

In the function R(d), λ is the frequency, $G(d) = m^{-1} \sum_{j=1}^{m} \lambda_j^{2d} I_j$, m is some integer that is small relative to n and $I_j = I_x(\lambda_j)$ the periodogram of x_t evaluated at frequency λ_j. The process $m^{-1/2} \sum_{j=1}^{mr} v_j (I_j \lambda_j^{2d_o} / G_0) - 1$ satisfies a functional central limit theorem and thus is uniformly $O_p(1)$ under the null hypothesis. Thus Qu suggests the following Wald test statistic:

$$W = \sup_{r\in[\epsilon,1]} \left(\sum_{j=1}^{m} m_j^2\right)^{-1/2} \left| \sum_{i=1}^{mr} v_j \left(\frac{I_j}{G\hat{d}_w \lambda_j^{-2\hat{d}_w}} - 1\right) \right| \quad (6)$$

where $\widehat{d}_w$ is the local Whittle estimate of d using m frequency components and ε is a small trimming parameter, and G_o is the true value of G; when treated as a process in r satisfies a functional central limit theorem and $O_p(1)$ is of under the null hypothesis of long memory in the series x_t . Whereas, if the series xt is short memory and affected by either regime change or a trend, the quantity diverges. Qu (2011) uses Monte-Carlo methods to get the 5% critical values of 1.252 when ε = 0.02 and 1.155 when ε = 0.05.

3.5 Volatility Spillover

DCC-MGARCH model is employed to examine the time-varying correlations among four precious metals to indicate the degree of financial integration among them. Engle (2002) introduced the DCC model which is an extension of the CCC-GARCH model developed by Bollerslev (1996). DCC model uses a two-step procedure. In the first step, the individual conditional variances are determined as univariate GARCH process and then the standardized residuals are used to calculate the conditional correlation matrix. The DCC-MGARCH model is a dynamic model with time-varying mean, variance and covariance of return series $r_{i,t}$ for precious metal *i* at time *t*, with the following equations:

$$r_{i,t} = \mu_t + \varepsilon_t$$

$$\mu_t = E(r_{i,t} \left| \psi_{t-1} \right.) \text{ and } \varepsilon_t \left| \psi_{t-1} \right. \sim N(0, H_t) \ , \quad (7)$$

where Ψt − 1 denotes the set of information available at time *t − 1.* The conditional variance–covariance matrix, H_t , can be constructed by the following equations:

$$H_t = D_t R_t D_t \quad (8)$$

$D_t = (\sqrt[2]{h_{ii,t}}, ..., \sqrt[2]{h_{NN,t}})'$ is a diagonal matrix of square root conditional variances. $h_{i,t}$ can be defined as $h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-i}^2 + \beta_i h_{i,t-1}$., where ω_i is a constant term and α_i is the ARCH effect and β_i is the GARCH effect. R_t is a time-varying conditional correlation matrix and it is stated as follows:

$$R_t = diag\{Q_t\}^{-1/2} Q_t diag\{Q_t\}^{-1/2} , \quad (9)$$

where $Q_t = \left[q_{ij,t} \right]$ is a $N \times N$ symmetric positive definite matrix given by:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\, \mu_{t-1}\mu'_{t-1} + \beta Q_{t-1}\,, \qquad (10)$$

where $\mu_t = (\mu_{1t}\mu_{2t\ldots}\mu_{Nt})'$ is the *N x1* vector of standardized residuals, $\bar{Q}$ is the *NxN* unconditional variance matrix of μ_t , α and β are non-negative scalar parameters.

The correlation estimator is

$$p_{ij,t} = \left(\frac{q_{ij,t}}{\sqrt{q_{ii,t}\, q_{jj,t}}} \right) \qquad (11)$$

The DCC-MGARCH model is estimated using the Quasi-Maximum Likelihood (QML) estimator proposed by Bollerslev and Wooldridge (1992). QML is a maximum likelihood model with a robust variance–covariance estimator.

4. Empirical Findings

Table 1 Descriptive Statistics for Spot Returns

	GOLD	SILVER	PLATINUM	PALLADIUM
Mean (%)	0.0495	0.0454	0.0350	0.0097
Min. (%)	-8.0627	-19.031	-18.248	-16.107
Max. (%)	9.1848	18.402	3.250	11.354
Std. Dev.(%)	1.19055	2.2029	1.5221	2.2083
Skewness	-0.0085	-0.6511	-0.2935	-0.331
Excess Kurtosis	6.2838	9.5791	12.954	4.7121
JB	5406.4***	12796***	23021***	3100.2***
ARCH(10)	23.532***	40.047***	25012***	23.648***
Q(10)	24.5687**	72.8126***	15.5022	28.2079***
Q^2(10)	406.871***	548.306***	390.942***	381.759***
Unit Root Tests				
ADF	-35.0536***	-36.8505***	-35.908***	-35.5782***
KPSS	0.0617646	0.0683195	0.0322056	0.466283
Observation	3632	3632	3632	3632

Notes: ***, **, * denote significance at 1%, 5% and 10% level, respectively. The critical values are -2.56572 (1%), -1.94093(5%), -1.61663(10%) for ADF test. The critical values are 0.739 (1%), 0.463 (5%), 0.347(10%) for KPSS test.

Table 1 summarizes the descriptive statistics for the spot gold, silver, platinum and palladium return series. Among the precious metals, gold has the highest return and palladium has the lowest return. The spot palladium has the highest standard deviation and the lowest return, which may make investors uncomfortable to use palladium in their portfolios. This result is consistent with Balcilar et al. (2015). The skewness is negative and kurtosis is above three, indicating a leptokurtic distribution. The Jarque–Bera test results suggest that all of the return series exhibit significant deviation from normality. ARCH (5) test results provide strong evidence of ARCH effects in all the precious metal return series. Furthermore, Table 1 documents that ADF test rejects the null hypothesis of unit root for all the return series at the 1% significance level. Similarly, KPSS test cannot reject the stationarity of the returns at the 1% significance level. All precious metal return series are therefore stationary.

Figure 1 Plots of daily returns for major precious metals

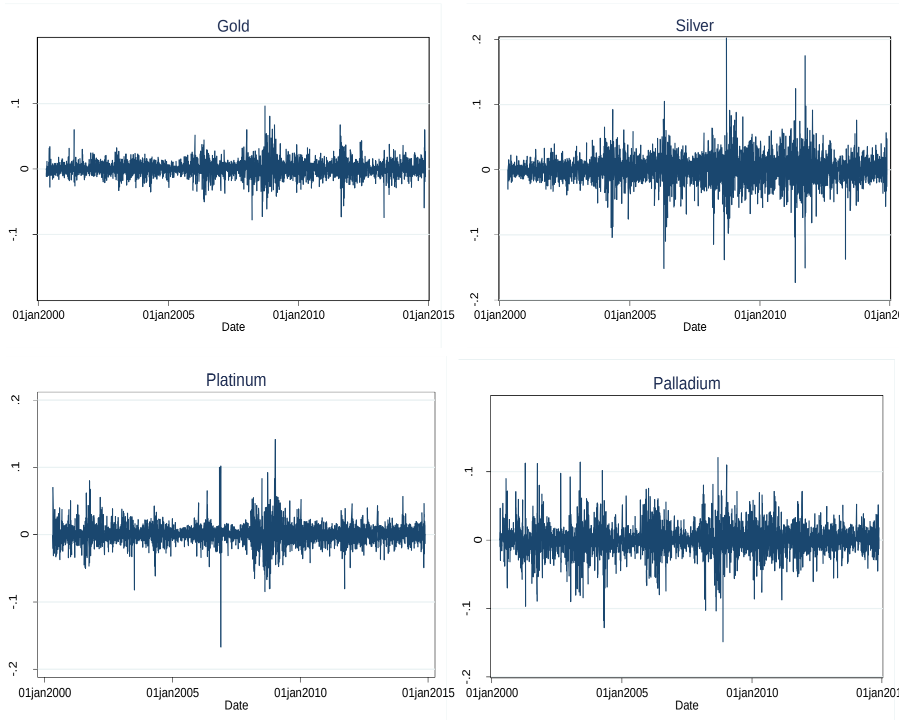

Figure 1 displays the plots of daily returns for gold, silver, platinum and palladium. The daily return series show high volatility during the 2007-2009 global financial crisis. The findings reflect that gold and silver returns have similar patterns, indicating that the prices of gold and silver move together. Among all precious metal returns, while platinum series have low volatility clustering, palladium series exhibit high volatility clustering property where periods of high volatility remains persistent for some time before switching. However, the question of whether the volatility persistence is strong enough to constitute long memory remains to be tested.

Table 2 Long Memory Tests

	Returns		Squared Returns	
	GPH	mGPH	GPH	mGPH
	$T^{0.5}$	$T^{0.5}$	$T^{0.5}$	$T^{0.5}$
Gold	0.0279	0.0180	0.1467***	0.334***
	[1.073]	[0.3823]	[5.627]	[7.083]
Silver	0.0071	-0.0085	0.1691***	0.2397***
	[0.2748]	[-0.1814]	[6.486]	[5.083]
Platinum	-0.0099	0.0580	0.1794***	0.2143***
	[-0.3823]	[1.231]	[6.88]	[4.54]
Palladium	0.0057	0.1283 ***	0.1937***	0.237***
	[0.220]	[2.72]	[7.428]	[5.025]

Notes: t-values are shown in brackets [ ]. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

Table 2 demonstrates the long memory test results for raw and squared returns. The findings show no evidence of long memory in the return series of gold, silver and platinum. However, there is a strong indication of long memory in palladium return series. The existence of long memory in return series suggests that palladium might not be a good hedge to achieve portfolio diversification. The results further indicate that long memory property exists in the squared returns of the precious metals. Since squared returns are used as proxy for volatility, the findings thus suggest that the volatility of precious metals would tend to be range-dependent and persistent. This may lead arbitrage opportunities for the investors. The evidence of long memory in squared returns is similar to the findings of Arouri et al. (2012).

Table 3 Structural Break Test Results

	Number of Breaks	Break Dates
Gold	6	18.04.2006 24.07.2006 14.03.2007 02.11.2007 08.08.2008 22.04.2009
Silver	2	17.09.2001 06.01.2004
Platinum	3	03.04.2002 02.11.2006 09.06.2009
Palladium	0	-

Table 3 reports the structural breaks using the modified ICSS algorithm. There are 6 structural breaks for gold, 2 breaks for silver, and 3 breaks for platinum. However, no statistically significant break was detected for palladium. This finding is consistent with Gil-Alana et al. (2015), who presented the evidence of structural breaks in almost all cases except palladium. The results also show large shifts in the volatility of the precious metals during the recent financial crisis. In particular, most of the breaks in the gold series are associated with the period of 2007-2009 global financial crisis, which hit gold prices at an all-time high. All break dates in silver and two break dates in platinum occurred before the recent financial crisis.

Table 4 Test of Long Memory versus Structural Breaks

	Qu(2011)		Shimotsu (2006)						
	W	*W*		$\bar{d}$		*W*		(PP)	(KPSS)
	(ε=0.02)	(ε=0.05)	$\hat{d}$	*b=2*	*b=4*	*b=2*	*b=4*	Z_t	η_u
Gold	0.1596	0.1596	0.7306	0.7346	0.7397	0.2927	0.8836	-0.9108*** (*-2.843*)	0.0817 (*0.454*)
Silver	0.1932	0.1932	0.7113	0.7108	0.7309	0.0007	3.5095	-1.0067*** (*-2.839*)	0.0719 (*0.454*)
Platinum	0.3976	0.2445	0.6817	0.6478	0.6458	5.0076	3.6899	-1.4267*** (*-2.825*)	0.0602 (*0.445*)
Palladium	1.1059	1.1059	0.7132	0.7161	0.7012	0.0093	2.8919	-1.1508*** (*-2.840*)	0.3240 (*0.452*)

Notes: Qu (2011) test based on the local Whittle likelihood, with two different trimming choices (Ɛ = 2% and Ɛ = 5%). The test of Shimotsu (2006) is based on sample splitting with 4 sub-samples. Z_t refers Phillips-Perron (PP) test and η_u refers Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. t-values are shown in parenthesis. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

We applied the tests of Shimotsu (2006) and Qu (2011) to test whether the long memory is spurious or not. The findings indicate that the null hypothesis of a true long memory process cannot be rejected. The evidence of long memory is thus not spurious for gold, silver, platinum and palladium. The results suggest that the long memory is true. The findings of Shimotsu (2006) and Qu (2011) tests are consistent with each other. The persistence we found in the conditional volatility of the precious metals is not due to the presence of structural breaks. Furthermore, it is evident that both PP and KPSS unit root tests show that the precious metal return series are stationary.

Figure 2 Time-varying Dynamic Conditional Correlations

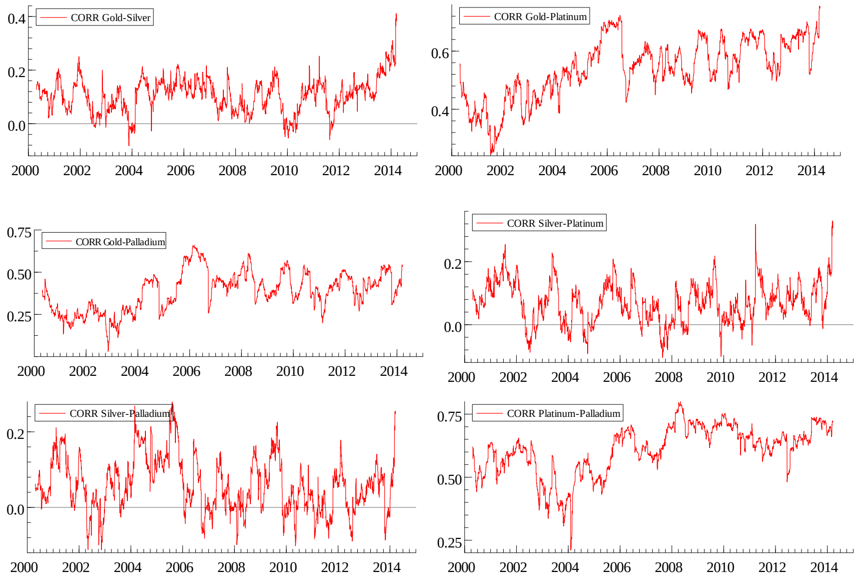

Figure 2 shows the evolution of the time-varying correlations among Russian precious metals. The conditional correlation between platinum and palladium increases, in particular, during the recent global financial crisis and the highest conditional correlation occurs between platinum and palladium. The conditional correlations for silver-platinum and silver-palladium are the lowest amongst others. Silver appears to be a potential instrument for investors in Russia who want to diversify their portfolios to cushion them against shocks.

Table 5 Estimation Results of DCC model with ARMA (1, 1)–GARCH (1, 1)

	Pre-crisis period				Post-crisis period			
	Gold	*Silver*	*Platinum*	*Palladium*	*Gold*	*Silver*	*Platinum*	*Palladium*
Panel A: 1-step, univariate GARCH estimates and univariate diagnostic tests								
Cst(M)	0.000424**	0.000038	0.000603***	-0.000803*	0.000342	0.000420	0.000313	0.000743**
	(0.0309)	(0.8907)	(0.0010)	(0.0873)	(0.2095)	(0.2721)	(0.2580)	(0.0399)
AR(1)	-0.453709 ***	-0.300668	0.931683 ***	-0.423699	0.036326	-0.041605	0.664659	-0.099279
	(0.0003)	(0.1088)	(0.0000)	(0.4136)	(0.6184)	(0.6728)	(0.3973)	(0.1383)
MA(1)	0.399245***	0.204237	-0.955923***	0.523375	-0.046158	-0.128109	-0.653454	0.087786
	(0.0017)	(0.2972)	(0.0000)	(0.2860)	(0.6350)	(0.1958)	(0.4277)	(0.1311)
$\varpi(10^4)$	2.624946**	0.011006	0.028262	0.266517	0.025934*	0.198918	0.014381	0.043017
	(0.0329)	(0.1840)	(0.3240)	(0.1038)	(0.0515)	(0.1283)	(0.1698)	(0.1250)
α	0.075745***	0.069409 ***	0.074329***	0.204947	0.063258***	0.089536***	0.056502***	0.065122***
	(0.0000)	(0.0014)	(0.0012)	(0.0105)	(0.0004)	(0.0040)	(0.0006)	(0.0004)
β	0.897369***	0.931411***	0.915991***	0.765656 ***	0.924355***	0.878409***	0.938611***	0.925837***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Panel B: 2-step, correlation estimates and multivariate diagnostic tests								
$p_{silver-gold}$	0.122139 (0.0441) **				0.091258 (0.0134) ***			
$p_{platinum-gold}$	0.428293 (0.0000) ***				0.647272 (0.0000) ***			
$p_{palladium-gold}$	0.359232 (0.0000) ***				0.484259 (0.0000) ***			
$p_{platinum-silver}$	0.073065 (0.1968)				0.079003 (0.0377) **			
$p_{palladium-silver}$	0.081405 (0.2064)				0.060187 (0.1010)			
$p_{palladium-platinum}$	0.473474 (0.0000) ***				0.717983 (0.0000) ***			
α	0.010477 (0.0002) ***				0.018267 (0.0000) ***			
β	0.983036 (0.0000) ***				0.939595 (0.0000) ***			
Li-McLeod(50)	1491.94 (0.0000) ***				1589.19 (0.0000) ***			
Hosking(50)	1492.07 (0.0000) ***				1385.70(0.0000) ***			
AIC	-23.573663				-23.052266			
Log Likelihood	19739.583				22600.168			

Notes: Li-McLeod and Hosking tests are the multivariate versions of Ljung–Box statistic of Hosking (1980) and Li and McLeod (1981), respectively. p-values are given in parenthesis. ***, **, * denote significance at 1%, 5% and 10% level, respectively.

Table 5 presents time-varying observable correlations obtained from DCC model of Engle (2002).[1] We split the sampling period into two parts: pre-crisis and post-crisis periods. Pre-crisis period is from 21 April 2000 to 31 December 2006. The post-crisis covers the period from 5 January 2007 to 21 November 2014.Sub-samples allow us to explore the changes in the dynamic correlation of stock returns of precious metals.

Our findings show that there is a highly significant positive dynamic conditional correlation among precious metals. This finding is in the line with Sensoy (2013), who stated that strong correlations among precious metals reduce the diversification benefits across them and indicate a convergence to a single asset class. This is true particularly following the recent financial crisis. With the exception of gold and silver, the dynamic correlations among other pairs of precious metals displayed an increasing trend in the post-crisis period. The correlation between gold and silver decreased in the post-crisis period. Furthermore, while the correlation between platinum and silver was not significant during the pre-crisis period, the correlation between these two metals increased significantly during the post-crisis period. These findings suggest that time variation plays a crucial role for volatility spillover among precious metals. In this context, our findings are in parallel to those of Cochran et al. (2012) who reported increase in the volatility in precious metals returns during the post global financial crisis.

The strongest, in magnitude, co-movements occur between the palladium–platinum, followed by platinum-gold, palladium-gold returns. The finding of the highest CCC between platinum and palladium is consistent with the findings of Hammoudeh et al. (2010). The high dynamic correlation between platinum and palladium suggests poor portfolio diversification benefits. The least effective hedging strategy among the precious metals is using platinum and palladium for hedging purpose. Indeed, it is not surprising to have the highest correlation between palladium and platinum as both of them are very similar metals in that they derive much of their value from industrial uses. Their differences occur due to density and price. Further, Russia is very influential on palladium and platinum metals markets, since it is the largest producer of palladium and ranked as second in the global production of platinum-group metals.

The findings further show no evidence of significant contagion between palladium and silver returns. It is important to note that there is either weak or no dynamic conditional correlation for each pair of precious metal returns when silver is involved. As a result, there is a great potential for international portfolio diversification by using silver.

[1] During our preliminary study, we employed two asymmetric GARCH models, which are based on the EGARCH and GJR models, respectively. The results were similar to those presented in Table 5. While the estimates of the EGARCH and GJR models are close to those of the DCC-GARCH model, the AIC and BIC criteria for the DCC-GARCH model were smaller than those of the EGARCH and GJR models. Since both the AIC and BIC criteria favor the DCC-GARCH model relative to the EGARCH and GJRJ models, we used DCC-GARCH model.

5. Conclusion

The objective of this paper is to examine the volatility dynamics of four precious metals (gold, silver, platinum, and palladium) that are traded in Russia from 21st April 2000 through 21st November 2014. Since Russia is rich in precious metals and was recently involved in aggressive gold purchases, investigating the volatility dynamics of the precious market led us to focus on two major questions. First, is there a long memory property and structural break in returns and volatility series of precious metals in Russia? Second, do precious metals get strongly correlated with each other?

Our empirical findings show that while there is no evidence of long memory in the return series of precious metals except palladium, there is a strong long memory property in the volatility series of all precious metals. This finding suggests that palladium might not be a good hedging instrument for portfolio diversification. Furthermore, using the structural break tests, we detected 2 breaks gold, 2 breaks in silver and 2 breaks in platinum. There is no break for palladium. Most of the breaks were associated with the recent global financial crisis. We also found that when the structural breaks are controlled, the conclusion of long memory property remains the same. This finding implies that the evidence of long memory is thus not spurious.

Furthermore, we analyzed the consistent conditional correlations of precious metal returns. In general, there are significant and positive correlations among precious metals. In particular, the strongest correlation occurs between palladium and platinum in a portfolio of precious metals. Increased correlation across precious metals reduces their diversification benefits in a portfolio. Considering the recent global financial crisis, the findings show that the dynamic correlation levels increased for the precious metal pairs in the post-crisis period. The exceptions are silver-gold and silver-platinum pairs, where the magnitudes of the correlations decreased slightly. The findings further reveal the fact that there is either weak or no dynamic conditional correlation for precious metals pairs when silver is involved. Considering the investors that hold different precious metals in their portfolios, investors may consider including silver into their investment portfolios due to its low correlations with other precious metals.

We believe that our findings provide a better understanding of the Russian precious metals market and will be helpful for investors and portfolio managers. For the future studies, it would be interesting to examine whether precious metals converge to a single asset class, in particular, in times of economic downturns or not. Further research may explore this question with more sophisticated techniques.

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