Research Article | Open Access

Volume 2016 | Article ID 2361954 | https://doi.org/10.1155/2016/2361954

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Do Scarce Precious Metals Equate to Safe Harbor Investments? The Case of Platinum and Palladium

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Academic Editor: Jean Paul Chavas

Published: 10 Jan 2016

Abstract

This research establishes the predictability and safe harbor properties of two scarce precious metals, namely, platinum and palladium. Utilizing their spot prices, the study concludes intermediate memory in the return structures of both precious metals, which implies the instability of platinum and palladium returns' persistency in the long run. However, both the ARFIMA-FIGARCH and the ARFIMA-FIAPARCH models confirm long-memory properties in the volatility of the two spot prices. The leverage effects phenomenon is not also present based on the ARFIMA-APARCH and ARFIMA-FIAPARCH models, which may possibly conclude the resilience of both precious metals against increased volatility. However, further tests proved that only platinum has a symmetric volatility response to

Platinum and palladium are both precious metals, which attract huge jewelers for ornaments or plain store of value, and industrial metals, which have various applications in automobile, electronic, and even dentistry components. Investment analysts argue that the short-term prospects of the metals are bright, because of their relatively current low prices per ounce, which once peaked at US$ 2,200/ounce in 2008 for platinum and US$ 1,100/ounce in 2000 for palladium. Demand is also more likely to rise because of the forecasted increased demand in the automobile industry especially in the emerging markets of China and India because platinum is used primarily for catalytic converters. Also, palladium is slowly replacing platinum as a lower-cost material from the past two decades, since it can basically perform the same function as platinum in catalytic converters. However, researchers argue that, in the longer term, platinum might be a better performer than palladium based on Johnson Matthey Plc Executive Summary Report of 2013. The research firm forecasts that gross platinum demand will rise by around 4.9% to a record of 8.42 million ounces, but gross palladium demand might fall by 3.4% to 9.63 million ounces because of slowing demand in diesel engines' catalytic converters due to more stern emission regulations.

The performance of these two precious metals as investments in the long run is tested in this study. Understanding return and volatility characteristics of platinum and palladium spot prices is important because persistent changes in their time-series structures can expose investors and hedgers alike to risk especially when weak industry demand and instability of supply occur. Accurate modeling of their time-series return and volatility characteristics can become a major concern if supply deficit continues to increase for platinum and decrease for palladium. The possible spillover to the globalized commodity precious metals markets made scholars and practitioners more interested in knowing the predictability and asymmetric volatility properties of platinum and palladium.

The predictability of precious metals under study can be determined by the positive dependence or the so-called long-memory process, which models the presence of a persistent temporal dependence among distant time-series data in returns and volatility. On the other hand, the asymmetric volatility property of the platinum and palladium data series describes the negative correlation between their returns and innovations in volatility. This property is commonly connected to the leverage effects phenomenon, because negative changes are often followed by future higher volatility than positive innovations. These data characteristics have been seen in stock returns (e.g., [2, 3]), exchange rates (e.g., [4, 5]), commodities [6, 7], exchange-traded funds (ETFs) (e.g., [8, 9]), and exchange-traded notes (ETNs) (e.g., [10]). However, the literature has yet to characterize the predictability and asymmetric volatility of platinum and palladium spot prices. The study is motivated by the recent surge in the application of fractionally integrated (FI) long-memory and asymmetric volatility models in financial time-series. This research is also inspired by the possible upward momentum in the prices of platinum and palladium because of the steadying supply beginning the second quarter of 2014.

Section 3 presents the empirical results; and Section 4 gives the conclusion.

2. Data and Methodology

This research analyzes daily London closing prices of platinum and palladium from the Johnson Matthey Base Price database downloaded in Quandl.com website from July 2, 1992, to May 23, 2014. The platinum data has a total of 5,535 data points, and palladium has a total of 5,531 observations. The returns series of both precious metal prices were computed as $y_t = 100(\log p_t - \log p_{t-1})$, where p_t represents the price at time t. The financial time-series data were modeled by ARFIMA-GARCH, ARFIMA-APARCH, ARFIMA-FIGARCH, and ARFIMA-FIAPARCH processes and are explained below.

The ARFIMA (p, d, q) model proposes the difference parameter (d) as noninteger and suggests the FI process $I(d)$ in the conditional mean. The model was introduced by Granger and Joyeux [13] and Hosking [14], which offered the initial testing of the long-memory process. The model complies with both stationary and invariability conditions and can be represented as

$$\phi(L)(1-L)^d(X_t-\mu) = \theta(L)\varepsilon_t, \varepsilon_t = z_{t\sigma_t}, z_t \sim N(0.1), \quad (1)$$

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$$\varepsilon_t = z_{t\sigma_t}, z_t \sim N(0.1),$$

where d denotes a fractional integration real number parameter, μ corresponds to the conditional mean, L represents the lag operator, and ε_t denotes a white noise residual. The $(1-L)^d$ function corresponds to the fractional differencing lag operator. The AR and the MA processes have all roots outside the unit circle and can be shown as $\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_P L^P$ and $\theta(L) = 1 - \theta_1 L - \theta_2 L^2 - \cdots - \theta_P L^P$, respectively.

The ARFIMA model is said to be stationary when $-0.5 < d < 0.5$, where the effect of shocks to ε_t decays at a gradual rate to zero. The model becomes nonstationary when $d \geq 0.5$ and stationary but a noninvertible process when $d \leq -0.5$, which means that the data time-series is impossible to model by any AR process. With regard to the modeling of data dependencies, the ARFIMA model represents a short memory if $d = 0$, where the effect of shocks decays geometrically; and a unit root process is shown when $d = 1$. Furthermore, the model has a positive dependence among distant observations or the so-called long-memory process if $0 < d < 0.5$; and it also has an estimating the optimal power term rather than imposing a structure on the data. The APARCH model can be expressed as

$$\sigma_t^{\delta} = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left(\left|\varepsilon_{t-i}\right| - \gamma_i \varepsilon_{t-i}\right)^{\delta} \quad (5)$$

$$\sigma_t^{\delta} = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left(\left|\varepsilon_{t-i}\right| - \gamma_i \varepsilon_{t-i}\right)^{\delta} + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^{\delta}, \quad (5)$$

$$+ \sum_{j=1}^{p} \beta_j \sigma_{t-1}^{\delta},$$

where $\alpha_0 > 0, \delta \geq 0, \beta_j \geq 0, \alpha_i \geq 0$, and $-1 < \gamma_i < 1$.

The APARCH model offers the flexibility of a varying exponent δ with the asymmetry coefficient γ_i to account for the leverage effect. The model can be reduced to the ARCH model when $\delta = 2$, $\gamma_i = 0$ $(i = 1, \ldots, p)$, and $\beta_j = 0$ $(j = 1, \ldots, p)$; GARCH model when $\delta = 2$ and $\gamma_i = 0$ $(i = 1, \ldots, p)$; and the GJR when $\delta = 2$.

The FIGARCH (p, d, q) model extends the traditional GARCH model and allows the distinguishing parameter (d) to be noninteger. The model was introduced by Baillie et al. [18], which offers greater flexibility by capturing short, intermediate, and long memory in the volatility of financial time-series. The FIGARCH model can be expressed as

$$\left[\phi(L)(1-L)^d\right]\varepsilon_t^2 \quad (6)$$

$$\left[\phi(L)(1-L)^d\right]\varepsilon_t^2 = \omega + \left[1-\beta(L)\right]\left(\varepsilon_t^2 - \sigma_t^2\right), \quad (6)$$

$$= \omega + \left[1-\beta(L)\right]\left(\varepsilon_t^2 - \sigma_t^2\right),$$

where d represents a fractional integration parameter, L denotes the lag operator, and ε_t corresponds to a white noise residual process; $(1 - L)^d$ represents the fractional differencing operator; and $\phi(L)$ denotes an infinite summation, which has to be truncated. The model has a long-memory process when $0 < d < 1$, which allows more flexibility in modeling the conditional variance rather than the mean. The FIGARCH process is reduced to the GARCH model when $d = 0$.

The FIAPARCH (p, d, q) model also extends the GARCH process by capturing volatility asymmetry aside from the long-memory attribute in the conditional variance. The model was introduced by Tse [19] and is considered superior to the FIGARCH process through the improvement in volatility with the function $(|\varepsilon_t| - \gamma\varepsilon_t)^{\delta}$, which can be written as follows:

are under a nonnormal distribution assumption.

Table 1

The sample size and period of London gold price fixing.

Table 2 illustrates the use of Augmented Dickey-Fuller test to examine the stationarity of the platinum and palladium returns and the minimum value of the Akaike Information Criterion to identify the orders of the models. Both precious metals' returns have no serial correlation, based on the results of the Lagrange Multiplier (LM) test. This study also used the ARCH-LM process to test the ARCH effect and eliminate heteroscedasticity in the volatility of the data; the test also illustrates that the GARCH models can be applied in both the platinum and palladium price returns.

Table 2

Summary statistics of ARMA and GARCH filtering.

Tables 3(a) and 3(b) compare the findings of lagged returns and volatilities from the four combinations of models for platinum and palladium spot prices. Majority of the estimated values illustrate that significant lagged conditional variances of a_n and ψ_n are relatively stronger than those of significant lagged mean returns of a_n and θ_n. These outcomes suggest that both the short- and long-memory models for both precious metals also consent to the greater influence of volatility on current innovations. However, both the ARFIMA-APARCH and ARFIMA-FIAPARCH models agree that although volatility has stronger effect, there is an absence of the leverage effects phenomenon with the significant positive values of the delta (δ) parameter. The study concludes that both platinum and palladium may possibly be immune to greater risks brought about by increased volatility, which normally affects other instruments like what Niarchos et al. [21] demonstrated in stock markets, Huang and Yang [22] in exchange rates, Xu and Fung [23] in precious metals futures, and Chen and Huang [24] using ETFs.

which is twice that of palladium, and extreme durability make it more in demand for heavy industrial use and luxurious jewelries for ornaments and investments. On the other hand, palladium in catalytic converters in diesel engines, which comprises 68% of palladium's use, has been declining because of more stringent emissions regulations against pollution caused by diesel automobiles. The location of platinum's production is also more stable, 77% of which come from South Africa and only 13% comes from Russia, unlike palladium's production of which 40% comes from South Africa and 44% from Russia based on the latest report of US Geological Survey of 2012. The political instability in Russia makes the palladium's prices more volatile, while the huge amount of platinum's production in South Africa makes platinum's prices more stable. Empirical results using the short-memory model ARFIMA-APARCH in the volatility contradict the initial findings of Batten et al. [11] in concluding that platinum behaves more like a financial market instrument, which is not immune to economic shocks. However, given the relative scarcity, established demand, and stable supply of platinum, this paper concludes that precious metal can be a safe harbor investment in relation to palladium. Comparing the two short-memory models in volatility, the log-likelihood value consistently points to the combined ARFIMA-APARCH models as the best fitting model to characterize both precious metals' prices compared to utilizing the ARFIMA-GARCH models, which also justifies the symmetric volatility response property of platinum prices.

Table 5 illustrates the results of the two methodologies with long memory on volatility. The ARFIMA-FIGARCH models find intermediate memory in the return structures of platinum (−0.053 significant at the 5% level), and this is also confirmed by the ARFIMA-FIAPARCH models (−0.054 significant at the 5% level). However, neither of the models established intermediate memory in palladium because of insignificant results. These findings are again consistent with the initial findings of Arouri et al. [1], which means that returns property of platinum is antipersistent and will more likely change in the succeeding trading periods. Based on the intermediate-memory findings, it is advised that traders, in order to gain abnormal returns, should still be in constant lookout of market corrections. Furthermore, both the ARFIMA-FIGARCH and ARFIMA-FIAPARCH models found long-memory properties in the volatility of platinum and palladium (all significant at the 1% level), which means that their volatility structures are predictable and can pose a challenge against Fama's [12] weak-form EMH. The ARFIMA-FIAPARCH models also claim that platinum has a symmetric volatility response to shocks with the presence of negative gamma (−0.090 significant at the 10% level) coefficient, which is consistent with the earlier findings of ARFIMA-APARCH models. Aside from the consistent findings from the two APARCH models, which contradict the initial conclusions of Batten et al. [11], this result also means that negative and positive shocks have equal effects on platinum returns and volatilities, implying that platinum can be safe harbor investment able to withstand economic and financial risks.

This study determines platinum's and palladium's predictability through the long-memory process and safe harbor properties through the asymmetric volatility properties in returns and volatilities. The ARFIMA-GARCH and ARFIMA-FIGARCH models find intermediate memory in the return structures of both platinum and palladium, and both ARFIMA-APARCH and the ARFIMA-FIAPARCH models confirm the result for platinum, but not for palladium. Both models also found long-memory properties in the volatility of platinum and palladium implying the predictability in their volatility structures. With regard to the leverage effects phenomenon, both the ARFIMA-APARCH and ARFIMA-FIAPARCH models confirm the absence of the leverage effects with the significant positive values of the delta (δ) parameter, which may possibly conclude the resilience of both precious metals against increased volatility. However, further tests proved that only platinum has a symmetric volatility response to shocks with the presence of negative gamma parameter, which is consistent with the earlier findings of ARFIMA-APARCH models further proving that only platinum can be a safe harbor investment, because negative and positive shocks have equal effects on their volatilities.

The economic significance of these results is connected to the more stable demand of platinum from automotive manufacturers, jewelers, and industrial users and to being sourced in a comparatively safer and established location in South Africa compared to Russian mines. The paper recommends that platinum investors be not worried of economic and supply shocks and should have longer investing time horizons in buying the precious metal. Comparing the four models utilized, the log-likelihood value consistently points to the combined ARFIMA-FIAPARCH models as the best fitting model to characterize both precious metals' prices.

The paper acknowledges some limitations that future studies can consider. First, the paper restricted its models in not considering the recent subprime mortgage crisis or other related economic crises for possible structural break tests. Lastly, other econometric methods like that of other FI models like HYGARCH and FIEGARCH can be applied to these precious metals to determine other aspects of the long-memory and leverage effects phenomena, respectively. These limitations can provide future research avenues and can step on the contributions established by this paper regarding the predictability and safe haven properties of platinum and palladium spot prices.

Conflict of Interests

The author declares that there is no conflict of interests regarding the publication of this paper.

FIGARCH models of daily exchange rates," *Applied Financial Economics*, vol. 12, no. 8, pp. 589–600, 2002.
View at: Publisher Site | Google Scholar

6. K. Choi and S. Hammoudeh, "Long memory in oil and refined products markets," *The Energy Journal*, vol. 30, no. 2, pp. 97–116, 2009.
View at: Google Scholar
7. C. Kyrtsou, W. C. Labys, and M. Terraza, "Noisy chaotic dynamics in commodity markets," *Empirical Economics*, vol. 29, no. 3, pp. 489–502, 2004.
View at: Publisher Site | Google Scholar
8. G. G. Rompotis, "Predictable patterns in ETFs' return and tracking error," *Studies in Economics and Finance*, vol. 28, no. 1, pp. 14–35, 2011.
View at: Publisher Site | Google Scholar
9. J. H. Chen and J. F. Diaz, "Spillover and leverage effects of faith-based exchange-traded funds," *Journal of Business and Policy Research*, vol. 7, no. 2, pp. 1–12, 2013.
View at: Google Scholar
10. J. F. T. Diaz and A. Masa, "Positive dependence and volatility asymmetry properties of the largest exchange-traded notes (ETNs)," *Euro-Asian Journal of Economics and Finance*, vol. 2, no. 2, pp. 100–107, 2014.
View at: Google Scholar
11. J. A. Batten, C. Ciner, and B. M. Lucey, "The macroeconomic determinants of volatility in precious metals markets," *Resources Policy*, vol. 35, no. 2, pp. 65–71, 2010.
View at: Publisher Site | Google Scholar
12. E. Fama, "Efficient capital markets: a review of theory and empirical work," *The Journal of Finance*, vol. 25, no. 2, pp. 383–417, 1970.
View at: Publisher Site | Google Scholar
13. C. W. Granger and R. Joyeux, "An introduction to long-memory time series models and fractional

Econometrics, vol. 15, no. 1, pp. 49–53, 1998.
View at: Publisher Site | Google Scholar

20. H. Markowitz, “Portfolio selection,” *The Journal of Finance*, vol. 7, no. 1, pp. 77–91, 1952.
View at: Publisher Site | Google Scholar
21. N. Niarchos, Y. Tse, C. Wu, and A. Young, “International transmission of information: a study of the relationship between the U.S. and Greek stock markets,” *Multinational Finance Journal*, vol. 3, no. 1, pp. 19–40, 1999.
View at: Publisher Site | Google Scholar
22. B.-N. Huang and C. W. Yang, “Volatility of changes in G-5 exchange rates and its market transmission mechanism,” *International Journal of Finance and Economics*, vol. 7, no. 1, pp. 37–50, 2002.
View at: Publisher Site | Google Scholar
23. X. E. Xu and H.-G. Fung, “Cross-market linkages between U.S. and Japanese precious metals futures trading,” *Journal of International Financial Markets, Institutions and Money*, vol. 15, no. 2, pp. 107–124, 2005.
View at: Publisher Site | Google Scholar
24. J.-H. Chen and C.-Y. Huang, “An analysis of the spillover effects of exchange-traded funds,” *Applied Economics*, vol. 42, no. 9, pp. 1155–1168, 2010.
View at: Publisher Site | Google Scholar
25. B. Ruzgar and I. Kale, “The use of ARCH and GARCH models for estimating and forecasting volatility,” *Kocaeli Üniversitesi Sosyal Bilimler Enstitüsü Dergisi*, vol. 14, no. 2, pp. 78–109, 2007.
View at: Google Scholar
26. R. Tansuchat, C. L. Chang, and M. McAleer, *Modelling Long Memory Volatility in Agricultural Commodity Futures Returns*, 2009.
27. H. Goudarzi, “Modeling long memory in the indian stock market using fractionally integrated EGARCH model,” *International Journal of Trade, Economics and Finance*, vol. 1, no. 3, pp. 231–237, 2010.