Navarra Center for International Development

Working Paper nº 06/2015

PERSISTENCE OF PRECIOUS METAL PRICES: A FRACTIONAL INTEGRATION APPROACH WITH STRUCTURAL BREAKS

Luis A. Gil-Alana
NCID, University of Navarra, Pamplona, Spain

Shinhye Chang
University of Pretoria, Pretoria, South Africa

Mehmet Balcilar
Eastern Mediterranean University, Famagusta, Northern Cyprus, Turkey
University of Pretoria, Pretoria, South Africa

Goodness C. Aye
University of Pretoria, Pretoria, South Africa

and

Rangan Gupta
University of Pretoria, Pretoria, South Africa

Navarra Center for International Development
WP-06/2015

Persistence of precious metal prices: A fractional integration approach with structural breaks

Luis A. Gil-Alana, Shinhye Chang, Mehmet Balcilar, Goodness C. Aye and Rangan Gupta

Working Paper No. 06/2015
April 2015

ABSTRACT

This paper analyses the statistical properties of five major precious metal prices (gold, silver, rhodium, palladium and platinum) based on a fractional integration modelling framework while identifying structural breaks. We use monthly data from 1972:1 to 2013:12. Our results indicate orders of integration that are equal to or greater than 1 (long memory) in all cases except for silver and palladium where we find strong evidence of mean reversion with a parametric and semiparametric method, respectively. Given some inconsistencies between the parametric and semiparametric results, we suspect the possibility of structural breaks and our results show evidence of structural breaks in almost all cases except palladium. However, after accounting for structural breaks, we find evidence of an increase in the degree of persistence across time in the majority of cases. This implies that in general, shocks to these precious metals will be permanent requiring strong policy measures to return the series to their equilibrium levels in the event of negative shocks.

JEL Classification: C22, C14, O13

Keyword: Precious metal, unit root, long memory, structural break

Corresponding author: Luis A. Gil-Alana
Department of Economics & ICS_NCID
Universidad of Navarra
31080 Pamplona
Spain

1. Introduction

It has long been known that the main drivers of commodity prices are the result of compound interactions between macroeconomic factors such as demand, exchange rate, input prices as well as production processes (Soytas et al., 2009; Abbott et al., 2009). Moreover, the financialization of commodity markets has gradually exposed commodity prices to market-wide shocks (Tang and Xiong, 2012; Cai et al., 2001; Christie-David et al., 2000; Fama and French, 1988). These suggest that announcements of macroeconomic indicators may have an impact on commodity prices.

Unlike other commodities, the traditional perception of precious metals is that they generate a safe-haven against inflation (Baur and Lucey, 2010), thereby offering valuable diversification opportunities to investors and serving as a monetary medium when the market is uncertain, as well as having a wide range of manufacturing and industrial applications (e.g., Arouri et al., 2012; Batten et al., 2010; Christie-David et al., 2000; Ciner, 2001; Heemskerk, 2001). This is why the prices of precious metals have been considered as leading indicators of inflation or as a variable which can transmit the outlook of monetary policy to the economy (Greenspan, 1993). In other words, the pro-cyclical character of the demand for precious metals has underlined their roles as safe-havens and stores of value and may provide important information as to where the real economy is heading.

Macroeconomic and financial variables are known to exhibit some statistical characteristics that might have implications for policy makers, investors, producers, consumers, researchers and portfolio managers. Two of these properties that have been receiving increasing attention are persistence and structural breaks (Stock and Watson, 1996; Ang and Bekaert, 2002; Gil-Alana et al., 2013). Persistence measures the extent to which current short-term shocks lead to permanent future changes (Gil-Alana et al., 2013). Modelling the degree of persistence is important since it reflects the stability of the macroeconomic variable of the relevant country (Alexander and Barrow, 1994; Gil-Alana and Barros, 2014). A better understanding of past trends is required to improve our ability to anticipate future changes in precious metal prices. Furthermore, the persistence of precious metal price shocks may be transmitted to the other sectors of economy and macroeconomic aggregates where such shocks could be transitory or persistent.

Persistence can be determined by using unit root tests (e.g., Lee and Strazicich, 2003, 2004; Kapetanios et al., 2003; Bierens, 1997; Kwiatkowski et al., 1992; Phillips and Perron, 1988; Phillips, 1987). However, these unit root tests are limited by several caveats. Firstly, unit root tests have low power in the case of high persistence (Caporale and Pittis, 1999; Hansen 1995; Stock, 1994; Spanos, 1990), which results in the over-acceptance of the null hypothesis. This limitation of the unit root methods causes problems with measuring the exact number of differences, d, required to render a series stationary I(0). If d is fractional and constrained between 0 and 1, shocks will be transitory, yet the process of convergence will take longer when the value of d is close to one (Gil-Alana and Gupta, 2014).

A second problem is that testing for persistence without including structural breaks tends to provide overestimated persistence. Lee et al. (2006) note that structural breaks and trends are important considerations for the persistence of commodity prices. Historically commodity prices are characterised by up and down trends thereby showing evidence of volatility (Kroner et al., 1995; Brunetti and Gilbert, 1995; Pindyck, 2004; Gilbert, 2006; Fernandez, 2008). Volatility is a source of structural breaks (Calvo-Gonzalez et al., 2010; Deaton and Laroque, 1992). Precious metal markets in particular are very sensitive to fluctuations in supply, demand, and other macroeconomic conditions (Radetzki, 1989; Batten et al., 2010; Hammoudeh, et al., 2010). Moreover, episodes of world geo-political tensions, the Gulf wars, the Asian crisis, worries over Iranian nuclear plans, and the current global economic weaknesses also affect metal prices, which can cause sudden breaks in precious metal prices (Arouri et al., 2012). Ignoring structural breaks in economic time series can produce persistence or long memory effects and may have implications concerning the existence of higher order unconditional moments such as kurtosis, tail index, or forecasting (Mikosch and Stărică, 2004; Pesaran and Timmerman, 2004). There are also implications for asset allocation and risk management (Andreou and Ghysels, 2009). .

A considerable number of studies have dealt with commodity price dynamics and have shown significant volatility clustering and long-persistence of commodity price returns (Browne and Cronin, 2010; Agnolucci, 2009; Akram, 2009; Lescaroux, 2009; Sadorsky, 2006). However, only a few of them have studied the dynamics and distributional characteristics of precious metal prices (Cheung and Lai, 1993; Arouri et al, 2012; Ewing and Malik, 2013; Uludag and Lkhamazhapov, 2014). Cheung and Lai (1993) used the new rescaled range technique and show that gold returns exhibit long memory but the authors show that this is mostly due to a small number of observations relating to Middle Eastern political tension and the activities of the Hunt Brothers in 1979. Arouri et al (2012) used several parametric and semiparametric methods including ARFIMA- FIGARCH model and found strong evidence of long range dependence in the daily conditional return and volatility processes of four precious metals: gold, silver, platinum and palladium. Uludag and Lkhamazhapov (2014) used a similar approach as Arouri et al (2012), and found evidence of anti-persistence in spot returns and a lack of long memory property in gold futures returns . They concluded that long memory is a true feature of the data and not due to structural breaks. Ewing and Malik (2013) used the GARCH model and found evidence of persistence in the volatility of gold with and without structural breaks. In all these studies, structural breaks are exogenously determined.

The goal of this paper is to examine the persistence behaviour of five major precious metal prices (gold, silver, rhodium, palladium and platinum) within a fractional integration framework while identifying structural breaks. In this paper, we extend the existing literature on the dynamics of precious metal prices by examining the relevance of long memory and structural breaks in modelling the prices of five precious metals. Unlike, standard unit root tests, which can only indicate whether a series is stationary or not by looking at 0 or 1 for the orders of integration, and have low power especially in cases where the series is characterized by a fractional process (Diebold and Rudebusch, 1991; Hassler and Wolters, 1994; Lee and Schmidt, 1996; and more recently, Ben Nasr *et al.*, 2014), the long memory approach provides us with an exact measure of the degree of persistence. This in turn, can provide us with the time span that it would take for the shock to die off, if at all. However, long memory models are known to overestimate the degree of persistence of the series in the presence of structural breaks (Cheung, 1993; Diebold and Inoue, 2001; and more recently, Ben Nasr *et al.*, 2014), which are very likely in our case as it covers over four decades of monthly data covering the period of 1972:1-2013:12. We employ the method of Gil-Alana (2008) which enables us to endogenously determine the number of breaks and the break dates along with the fractional differencing parameter for each subsample. Our paper thus established a way to understand the distributional characteristics of precious metal prices and has important implications for portfolio investment and policy decisions.

The remaining part of the paper is organized as follows: Section 2 describes the model. Section 3 presents the data and the empirical results and Section 4 provides some concluding remarks.

2. Methodology

We use techniques based on the concept of fractional integration, which means that the number of differences required to render a series I(0) stationary may be a fractional value rather than an integer as is the standard case in the time series literature. A given time series x_t, $t = 1,2,...,$, is said to follow an integrated of order *d* process (and denoted as $x_t \approx I(d)$) if

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, ..., \qquad (1)$$

where *d* can be any real value, *L* is the lag-operator ($Lx_t = x_{t-1}$) and u_t is I(0), defined for our purposes as a covariance stationary process with a spectral density function that is positive and finite at the zero frequency. Thus, u_t may display some type of time dependence of the weakly form, i.e., the type of an AutoRegressive Moving Average (ARMA) form such that, for example, if u_t is ARMA(p, q), x_t is said to be ARFIMA(p, d, q).

Based on the specification in (1) different features can be observed depending on the value of *d*. Thus, if $d = 0$ in (1), $x_t = u_t$ and the process is said to be short memory or I(0). In this case, if u_t is ARMA, the autocorrelations decay exponentially fast. On the other hand, if $d > 0$ the process is said to be long memory, so-named due to the high degree of association between observations which are far distant in time. In this context, if $d < 0.5$ the process is still covariance stationary and the autocorrelations decay hyperbolically fast. As long as *d* is smaller than 1, the process is mean reverting with shocks disappearing in the long run, contrary to what happens with $d \geq 1$ where shocks are expected to be permanent, i.e. lasting forever.

We estimate the fractional differencing parameter *d* by means of both parametric and semiparametric techniques. In the parametric approach, we use the Whittle function in the frequency domain (Dahlhaus, 1989), while in the semiparametric case, we use a Gaussian semiparametric method that also uses the Whittle function on a band of frequencies that degenerates to zero (Robinson, 1995).

Finally, due to the long span of the data (back to the early 70s) the possibility of structural breaks is also taken into account. This is a relevant issue in the context of fractional integration and long memory processes in general, since it has been argued by many authors (see for example, Cheung, 1993; Diebold and Inoue, 2001; and more recently, Ben Nasr *et al.*, 2014) that fractional integration may be an artificial artefact generated by the presence of breaks that are not taking into account in the models.

3. Data and Empirical results

The time series data examined in the paper are the monthly structure from 1972:1 to 2013:12 of the following metals: gold, silver, rhodium, palladium and platinum. The data is obtained from KITCO Metals Inc. (http://www.kitco.com). The results from unit root tests indicate that most of the series are non-stationary.[1]

Figure 1 displays the five log-transformed price series with their corresponding correlograms and periodograms. Apparently the five series are non-stationary, with the values in the correlograms decaying very slowly and observing large peaks in the periodograms at the smallest (zero) frequency.

[Insert Figures 1 and 2 about here]

Taking first differences (see Figure 2) of the series, the inflation rates may have now an appearance of stationarity, though we still observe some significant values at large lags in the correlograms, which may indicate that the first differenced series present a component of long memory behaviour.

Across Tables 1 – 3, we present the estimates of the fractional differencing parameter in a model given by:

$$y_t = \alpha + \beta t + x_t, \quad (1 - L)^d x_t = u_t, \quad t = 1, 2, \ldots \qquad (2)$$

[1] The standard unit root test results indicate that the precious metal prices have unit root. We cannot reject the null hypothesis – the series has a unit root -of the Augmented Dickey Fuller (ADF, 1979), the GLS-detrended Dickey-fuller (Elliot, Rothenberg, and Stock, 1996), Phillips-Perron (Phillips and Perron, 1988) and Ng and Perron (NP, 2001) unit root tests. We can reject the null hypothesis – the series is stationary- of the Kwiatkowksi, Phillips, Schmidt, and Shin (KPSS, 1992) unit root test. The results from Zivot-Andrews unit root test (Zivot and Andrews , 1992), Lumsdaine-Papell unit root test (Lumsdaine and Papell, 1997) and Lee-Strazicich unit root test (Lee and Strazicich, 2003) indicate that we cannot reject the null hypothesis of an evidence of stationarity with breaks. We also use two recently developed unit root tests: the Narayan and Popp (NP, 2010) test and the Liu and Narayan (LN, 2010) test which allow for two structural breaks in the data series. Using the NP test, we are able to reject the unit root null for Palladium at 5 percent level. Using the GARCH-based unit root test of LN, we find that the unit root null hypothesis – the series is non-stationary- cannot be rejected. Based on the nonlinear unit root test proposed by Kapetanios, Shin and Shell (KSS, 2003), we find that gold and silver have nonlinear characteristics. . These results are available upon request.

where y_t is the original time series (in our case the log-prices series), and α and β refers to the intercept and time trend respectively. We assume that u_t in Equation (2) is first a white noise process (in Table 1) and then autocorrelated. In the latter case, we suppose that u_t follows first the exponential spectral model of Bloomfield (1973), that approximates a nonparametrically ARMA process with a small number of parameters. The results using this specification are displayed in Table 2. Finally, given the monthly nature of the data, we also suppose that u_t follows a seasonal monthly AR(1) process (in Table 3). Here, in addition to the Whittle estimates of d, we also present the 95% region of non-rejection values of d using Robinson's (1994) Lagrange Multiplier (LM) tests, which are valid even in nonstationary (d $\geq$ 0.50) series.

[Insert Tables 1 - 3 about here]

For each table, we consider three different cases, corresponding to the cases of i) no deterministic terms ($\alpha = \beta = 0$), ii) an intercept (α unknown and $\beta = 0$), and iii) an intercept with a linear time trend (α and β unknown), and we have marked in bold type in the tables the selected cases according to the t-values of these deterministic components.

The first thing we notice in these three tables is that if u_t is white noise or seasonal AR, an intercept is simply required in the five series. However, if u_t follows the autocorrelated model of Bloomfield (1973) the time trend also seems required. Another remarkable feature is the fact that if u_t is white noise or seasonal AR, the estimated values of d in all the five series are above 1, rejecting the I(1) hypothesis in favour of higher degrees of integration. However, if u_t is Bloomfield, a different picture emerges, and the unit root null hypothesis is rejected in favour of mean reversion ($d < 1$) in the case of silver; the I(1) hypothesis cannot be rejected for gold, palladium and platinum; and it is rejected in favour of higher orders of integration ($d > 1$) in the case of rhodium. Thus, according to this last specification, heterogeneity exists in the orders of integration across the different precious metal log-prices series.

[Insert Table 4 about here]

Table 4 displays the estimates of d based on the "local" Whittle semiparametric method, so no functional form is imposed on u_t. However, we need to select a bandwidth number, which is the value appearing in the top row in the table. We have marked here in bold type the evidence of unit roots. The results indicate that for silver and rhodium the unit root null cannot be rejected for any bandwidth number. Up to the third bandwidth, the unit root null cannot be rejected for gold. This hypothesis is almost never rejected for gold and platinum, and evidence of mean reversion is now obtained in some cases for palladium. These results are not particularly consistent with those reported above for the parametric case, which may suggest that breaks might be producing inconsistency in our results. Thus, in the following section we employ a method that allows us to estimate breaks in the context of fractional integration. This approach, due to Gil-Alana (2008) enables us to endogenously determine the number of breaks and the break dates along with the fractional differencing parameter for each subsample.

[Insert Table 5 about here]

The results for each series are displayed in Tables 5 and 6 for the two cases of white noise and Bloomfield disturbances, and their corresponding estimated trends are presented in Figure 3 – 7. We observe first that the break dates take place at practically the same dates in the cases of uncorrelated and correlated errors. The only exception is Rhodium where one break is found with white noise disturbances but no breaks are observed with autocorrelated errors. Two break dates were found for gold (1980:4 and 2001:3) and silver (1980:4 and 2001:8); three breaks for platinum (1980:12, 1999:7 and 2007:10) and one single break for rhodium (1990:8 with white noise disturbances). For palladium and rhodium (in this case with autocorrelated errors) no statistically significant breaks are detected.

If we focus now on the orders of integration, the first thing we observe is that the values are generally higher if white noise errors are assumed. Thus, in all except one single case (Rhodium, first subsample) the estimated values of d are higher than 1. On the contrary, under autocorrelated errors, most of the values are below 1, in some cases, significantly lower and mean reversion (significant evidence of $d < 1$) is found in the first subsamples of gold, silver and platinum. Thus, in general, we notice an increase in the degree of dependence across time in the majority of cases.[2]

4. Conclusions

The recent global financial crisis has brought about an increase in the level of market uncertainty which leads market participants to think of precious metals as a safe haven from economic and political turbulence. Moreover, there is a growing interest on behalf of market participants to understand the distributional characteristics of assets. There are few papers in the literature that have addressed the issue of persistence of the prices of precious metals with a long memory model while accounting for structural breaks. This paper deals with the analysis of the statistical properties of five precious metal prices using fractional integration techniques. In particular we examine the monthly structure from 1972:1 to 2013:12 of the following metals: gold, silver, rhodium, palladium and platinum. Our results using both parametric and semiparametric techniques indicate that the orders of integration are equal to or higher than 1 in the majority of the cases and mean reversion is only obtained in the case of silver with a parametric method and palladium with the semiparametric method. Some

[2] We obtained quite similar results to the ones reported above, using the recently proposed time domain test of long-memory with structural breaks as proposed by Hassler and Meller (2014). They use a version of Bai and Perron's (1998) test applied to the Demetrescu et al.'s (2008) long memory model. This test also provides evidence of strong persistence across sub-samples in all the metal prices. The details of these results are available upon request from the authors.

inconsistencies between the parametric and semiparametric results suggest the possibility of structural breaks. Using the methodology developed by Gil-Alana (2008), we find evidence of three breaks in the case of platinum; two breaks for gold and silver, one (no) break for rhodium in the case of white noise errors (autocorrelated errors) and no break for palladium. With the structural breaks accounted for, we find the orders of integration are equal to or greater than 1 in all cases under the white noise error, except Rhodium in the first subsample, whereas under autocorrelated error most of the estimated values are below 1 with mean reversion obtained in the case of gold, silver and platinum in the first subsamples. Overall, we find evidence of long memory behaviour and hence long range dependence across time in the precious metals under investigation. Thus, in the event of exogenous shocks, the effects will be permanent in practically all cases and strong policy measures should be adopted to ensure the series return to their original trends.

The results have important policy implications for all stakeholders including traders, investors, portfolio managers, producers, consumers, researchers and policy makers. First, taking first differences of the prices of the five precious metals under the assumption of a unit root is required to make appropriate policy actions. Second, in the event of a negative shock, strong policy measures will have to be adopted to revert the precious metals (gold, silver, platinum, palladium, and rhodium) prices to their original trend. The persistence property of precious metal prices is vital for inflation targeting since the persistence property of precious metal prices is likely to affect the persistence property of the aggregate inflation of an economy. An increase (decrease) in precious metal demand would cause an increase (decrease) in precious metal prices, which would lead to an increase (decrease) in asset investment, which in turn would cause aggregate demand to increase (decrease), resulting in inflationary (deflationary) pressure. Shocks to the series might then have implications for economic variables such as interest rates, consumption, investment, and output growth.

Overall, understanding the properties of the precious metals has implications with regard to the widely held view of their being safe havens. Focusing only on the first subsample, one would conclude that all, except palladium, are good hedging instruments during market downturns since they have relatively short strays from their equilibrium levels. However, beyond the first subsample, all the precious metals do not necessarily prove good instruments for hedging.

References

Abbott, P. C., Hurt, C., & Tyner, W. E. (2009), What's driving food prices? March 2009 Update (No. 48495), Farm Foundation.

Agnolucci, P. (2009), Volatility in crude oil futures: a comparison of the predictive ability of GARCH and implied volatility models, Energy Economics, 31(2), 316-321.

Akram, Q. F. (2009), Commodity prices, interest rates and the dollar, Energy Economics, 31(6), 838-851.

Alexander, C., & Barrow, M. (1994), Seasonality and Cointegration of Regional House Prices in the UK, Urban Studies, 31:10, 1667-1698.

Andreou, E. & Ghysels, E. (2009), Structural breaks in financial time series, In Handbook of Financial Time Series. T.G. Andersen, R.A. Davis, J-P. Kreiß, and T. Mikosch (eds.). Springer.

Ang A & Bekaert G. (2002), Regime switches in interest rates, Journal of Business and Economic Statistics 20,163–182.

Arouri, M., Hammoudeh, S., Lahiani, A., & Nguyen, D. (2012), Long memory and structural breaks in modelling the return and volatility dynamics of precious metals, The Quarterly Review of Economics and Finance, 52, 207-218.

Bai, J. and P. Perron (1998). Estimating and testing linear models with multiple structural changes. *Econometrica 66*, 47–78.

Batten, J. A., Ciner, C., & Lucey, B. M. (2010), The macroeconomic determinants of volatility in precious metals markets, Resources Policy, 35, 65–71.

Baur, D. G., & Lucey, B. M. (2010), Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold, Financial Review, 45(2), 217-229.

Ben Nasr, A., Ajmi, A.N., & Gupta, R. (2014), Modeling the volatility of the Dow Jones Islamic market world index using a fractionally integrated time varying GARCH (FITVGARCH) model, Applied Financial Economics, 24, 993-1004.

Bierens, H. J. (1997), Testing the unit root with drift hypothesis against nonlinear trend stationarity, with an application to the US price level and interest rate, Journal of Econometrics, 81, 29-64.

Bloomfield, P., (1973), An exponential model in the spectrum of a scalar time series, Biometrika 60, 217-226.

Browne, F., & Cronin, D. (2010), Commodity prices, money and inflation, Journal of Economics and Business, 62, 331–345.

Brunetti, C., & Gilbert, C.L. (1995), Metals price volatility 1972–95, Resources Policy 21, 237–254.

Cai, J., Cheung, Y. L., & Wong, M. (2001), What moves the gold market?.Journal of Futures Markets, 21(3), 257-278.

Caporale, G. M., & Pittis, N. (1999), Unit root testing using covariates: some theory and evidence, Oxford Bulletin of Economics and Statistics, 61(4), 583-595.

Calvo-Gonzalez, O., Shankar, R., & Trezzi, R. (2010), Are commodity prices more volatile now? a long-run perspective, World Bank.

Cheung, Y-W & Lai, K.S. (1993), Do gold market returns have long memory? Financial Review, 28 (2), 181-202.

Christie-David, R., Chaudhry, M., & Koch, T. W. (2000), Do macroeconomics news releases affect gold and silver prices? Journal of Economics and Business, 52, 405–421.

Ciner, C. (2001), On the long-run relationship between gold and silver: a note, Global Financial Journal 12, 299–303.

Dahlhaus, R. (1989), Efficient parameter estimation for self-similar process. Annals of Statistics 17(4), 1749-1766.

Deaton, A., & Laroque, G. (1992), On the behaviour of commodity prices, Review of Economic Studies, 59, 1-23.

Demetrescu, M., V. Kuzin, and U. Hassler (2008). Long memory testing in the time domain. Econometric Theory 24, 176–215.

Dickey, D.A., & Fuller, W.A. (1979), Distribution of the estimators for autoregressive time series with a unit root, Journal of the American Statistical Society 75, 427–431.

Diebold, F.X., & Inoue, A. (2001), Long memory and regime switching, Journal of Econometrics, 105,131-159.

Diebold, F.S., & Rudebusch, G. (1991), On the power of Dickey-Fuller tests against fractional alternatives, Economic Letters, 35, 155-160.

Elliott, G., Rothenberg, T.J., & Stock, J.H. (1996), Efficient tests for an autoregressive unit root, Econometrica 64, 813–836.

Ewing, B., & Malik, F. (2013), Volatility transmission between gold and oil futures under structural breaks, International Review of Economics and Finance, 25, 113-121.

Fama, E.F., & French, K.R., (1988), Business cycles and the behaviour of metal prices, Journal of Finance, 43, 1075–1093.

Fernandez, V. (2008), The war on terror and its impact on the long-term volatility of financial markets, International Review of Financial Analysis 17, 1–26.

Gil-Alana, L.A. (2008), Fractional integration and structural breaks at unknown periods of time, Journal of Time Series Analysis 29, 163-185.

Gil-Alana, L.A., & Barros, C.P. (2012), An Analysis of USA House Price: Persistence, Breaks, and Outers, International Review Business in Social Sciences (forthcoming).

Gil-Alana, L. A., Aye, G. C., & Gupta, R. (2013), Testing for persistence in South African house prices, Journal of Real Estate Literature, 21, 293-314.

Gil-Alana, L. A., & Gupta, R. (2014), Persistence and Cycles in Historical Oil Prices Data, Energy Economics 45, 511-516.

Gilbert, C.L. (2006), Trends and volatility in agricultural commodity prices, A. Sarris and D. Hallam (Eds.), Cheltenham, Edward Elgar (Chapter 2).

Greenspan, A. (1993), The Fed aims for price stability, Challenge, 4-10.

Hammoudeh, S., & Yuan, Y. (2008), Metal volatility in presence of oil and interest rate shocks, Energy Economics, 30, 606–620.

Hammoudeh, S., Yuan, Y., McAleer, M., & Thompson, M. (2010), Precious metals-exchange rate volatility transmissions and hedging strategies. International Review of Economics and Finance, 20, 633-647.

Hansen, B. E. (1995), Rethinking the univariate approach to unit root testing -Using covariates to increase power, Econometric Theory, 111148-71.

Hassler, U., & Meller, B. (2014), Detecting multiple breaks in long memory the case of U.S. inflation, Empirical Economics, vol. 46, 653-680.

Hassler, U. and J. Wolters (1995) Long memory in inflation rates. International evidence, Journal of Business and Economic Statistics 13, 37-45

Heemskerk, M. (2001), Do international commodity prices drive natural resource booms? An empirical analysis of small-scale gold mining in Suriname, Ecological Economics, 39, 295–308.

Kapetanios, G., Shin, Y., & Snell, A. (2003), Testing for a unit root in the nonlinear STAR framework, Journal of Econometrics, 112, 359-379.

Kroner, K.F., Kneafsey D.P., & Claessens S. (1995), Forecasting volatility in commodity markets, Journal of Forecasting 14, 2, 77-95.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y., (1992), Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? Journal of Econometrics, 54, 159-178.

Lee, D., & Schmidt, P. (1996), On the power of the KPSS test of stationarity against fractionally integrated alternatives, Journal of Econometrics, 73, 285-302.

Lee, J., & Strazicich, M. C. (2004), Minimum LM unit root test with one structural break, Manuscript, Department of Economics, Appalachian State University.

Lee, J., & Strazicich, M. C. (2003), Minimum Lagrange multiplier unit root test with two structural breaks, Review of Economics and Statistics, 85(4), 1082-1089.

Lee, J., List, J.A., & Strazicich, M.C. (2006), Non-renewable resource prices: Deterministic or stochastic trends? Journal of Environmental Economics and Management, 51, 354-370.

Lescaroux, F. (2009), On the excess co-movement of commodity prices—A note about the role of fundamental factors in short-run dynamics, Energy Policy, 37, 3906–3913.

Liu, R., & Narayan, P.K. (2010), A new structural break unit root test based on a GARCH model.

Lumsdaine, R., & Papell, D. (1997), Multiple trend breaks and the unit root hypothesis, Review of Economics and Statistics, 79, 212-218.

Mikosch, T., & Stărică, C. (2004), Nonstationarities in financial time series, the long range dependence, and the IGARCH effects, Review of Economics and Statistics,
86, 378–390.

Ng, S., & Perron, P. (2001), Lag length selection and the construction of unit root tests with good size and power, Econometrica 69, 1519–1554.

Narayan, P.K., & Popp, S. (2010), A new unit root test with two structural breaks in level and slope at unknown time, Journal of Applied Statistics, DOI: 10.1080/02664760903039883.

Pesaran, M. H., & Timmermann, A. (2004), How costly is it to ignore breaks when forecasting the direction of a time series? International Journal of Forecasting, 20(3), 411-425.

Phillips, P. C. (1987), Time series regression with a unit root, Econometrica: Journal of the Econometric Society, 277-301.

Phillips, P. C., & Perron, P. (1988), Testing for a unit root in time series regression, Biometrika, 75(2), 335-346.

Pindyck, R.S. (2004), Volatility and commodity price dynamics, Journal of Futures Markets 24, 1029–1047.

Radetzki, M. (1989), Precious metals: The fundamental determinants of their price behaviour, Resources Policy, 15, 194-208.

Robinson, P.M. (1994). Efficient tests of nonstationary hypotheses, Journal of the American Statistical Association 89, 1420-1437.

Robinson, P.M. (1995), Gaussian semi-parametric estimation of long range dependence, Annals of Statistics 23, 1630-1661.

Sadorsky, P. (2006), Modeling and forecasting petroleum futures volatility, Energy Economics, 28, 467–488.

Soytas, U., Sari, R., Hammoudeh, S., & Hacihasanoglu, E. (2009), The oil prices, precious metal prices and macroeconomy in Turkey, Energy Policy, 37, 5557–5566.

Spanos, A. (1990), Unit roots and their dependence on the conditioning information set, Advances in Econometrics, 8, 271-92.

Stock, J. H. (1994), Unit roots, structural breaks and trends, in Engle, R. F. and McFadden, D. L. (eds.), Handbook of Econometrics, Vol. 4, chapter 46, pp. 2379-841, Elsevier, Amsterdam.

Stock J.H., & Watson M.W. (1996), Evidence on structural instability in macroeconomic time series relations, Journal of Business and Economic Statistics 14, 11–30.

Tang, K., & Xiong, W. (2012), Index investing and the financialization of commodities, Financial Analysts Journal, 68(6), 54-74.

Uludag, B.K., & Lkhamazhapov, Z. (2014), Long memory and structural breaks in the returns and volatility of Gold: evidence from Turkey, Applied Economics, 46, 31, 3777-3787.

Zivot, E., & Andrews, D. W. K. (1992), Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis, Journal of Business & Economic Statistics, 10(10), 251-270.

Figure 1: Original time series and their corresponding correlograms and periodograms

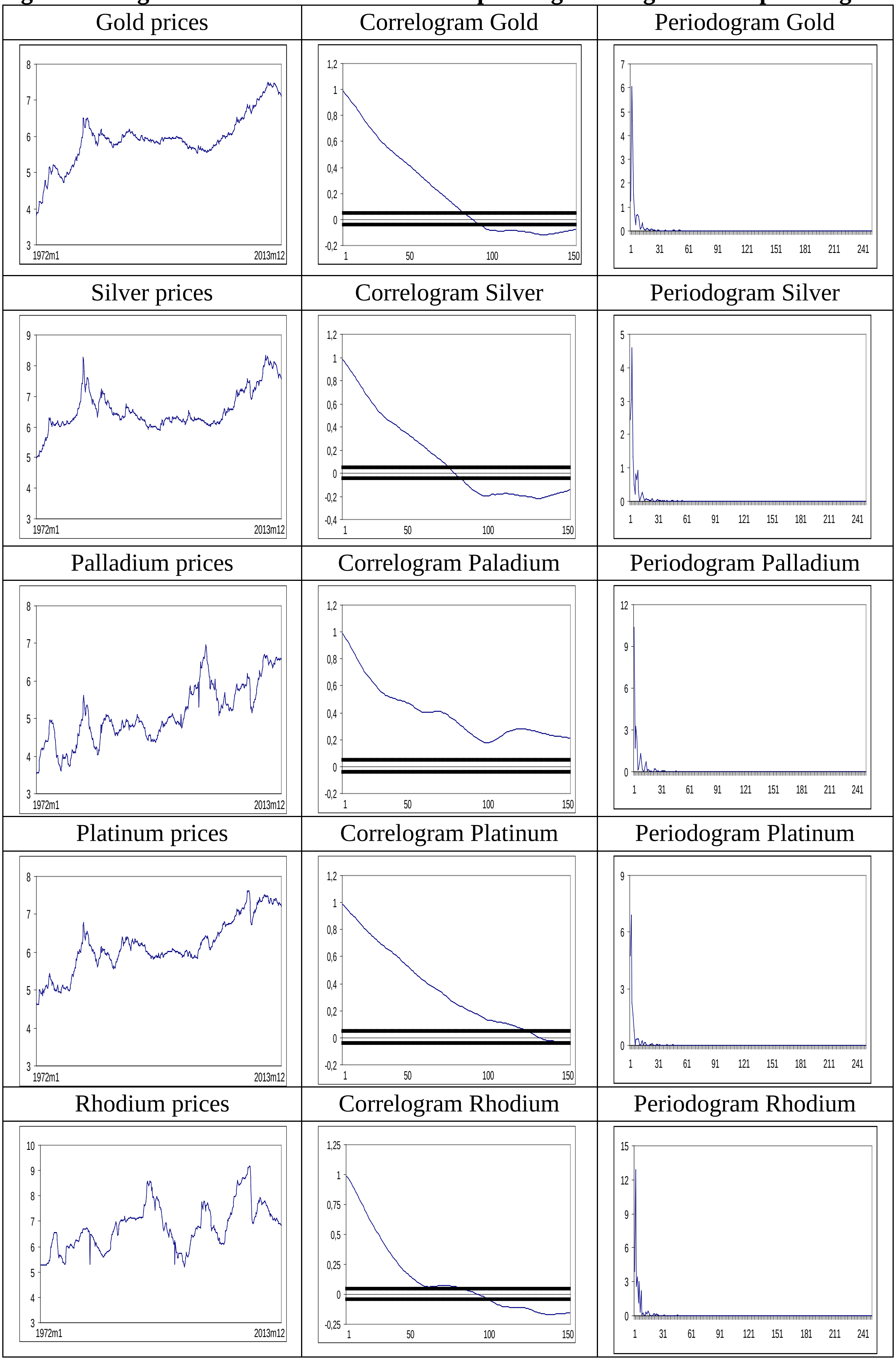

Figure 2: First differenced series and their corresponding correlograms and periodograms

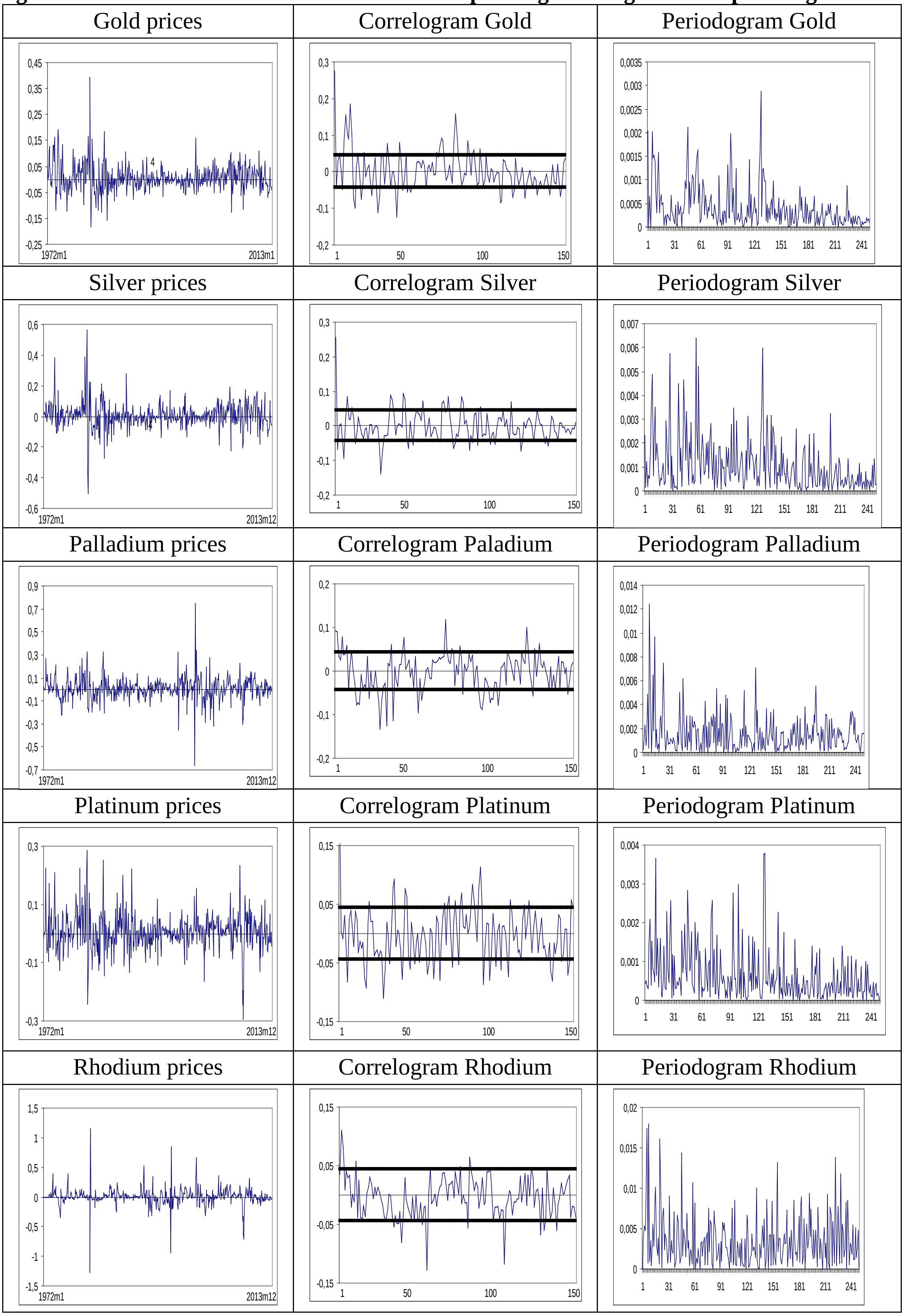

Table 1: Estimates of d under the assumption of white noise errors

	No regressors	An intercept	A linear time trend
Gold	1.01 (0.96, 1.08)	**1.18 (1.11, 1.27)**	1.18 (1.11, 1.26)
Silver	1.01 (0.95, 1.07)	**1.15 (1.07, 1.25)**	1.15 (1.07, 1.25)
Palladium	1.03 (0.97, 1.09)	**1.09 (1.03, 1.16)**	1.09 (1.03, 1.16)
Platinum	1.00 (0.94, 1.06)	**1.15 (1.07, 1.24)**	1.15 (1.07, 1.24)
Rhodium	1.01 (0.95, 1.07)	**1.06 (1.01, 1.13)**	1.06 (1.01, 1.13)

Note: Values in parenthesis are the 95% confidence intervals. The selected models according to the deterministic terms are indicated in bold type.

Table 2: Estimates of d under the assumption of Bloomfield-type errors

	No regressors	An intercept	A linear time trend
Gold	1.00 (0.93, 1.10)	**0.98 (0.91, 1.06)**	0.98 (0.91, 1.06)
Silver	0.98 (0.89, 1.07)	**0.88 (0.81, 0.98)**	0.89 (0.81, 0.98)
Palladium	1.05 (0.95, 1.15)	**1.10 (0.98, 1.24)**	1.10 (0.98, 1.24)
Platinum	1.00 (0.90, 1.09)	**0.93 (0.84, 1.06)**	0.93 (0.85, 1.06)
Rhodium	1.02 (0.91, 1.12)	**1.14 (1.03, 1.27)**	1.14 (1.03, 1.27)

Note: Values in parenthesis are the 95% confidence intervals. The selected models according to the deterministic terms are indicated in bold type.

Table 3: Estimates of d under the assumption of seasonal monthly AR(1) errors

	No regressors	An intercept	A linear time trend
Gold	1.01 (0.96, 1.07)	**1.18 (1.11, 1.27)**	1.17 (1.11, 1.26)
Silver	1.00 (0.95, 1.07)	**1.15 (1.07, 1.25)**	1.15 (1.07, 1.25)
Palladium	1.03 (0.98, 1.10)	**1.09 (1.03, 1.16)**	1.09 (1.03, 1.16)
Platinum	1.00 (0.95, 1.06)	**1.15 (1.07, 1.24)**	1.15 (1.07, 1.24)
Rhodium	1.01 (0.95, 1.07)	**1.07 (1.01, 1.13)**	1.07 (1.01, 1.13)

Note: Values in parenthesis are the 95% confidence intervals. The selected models according to the deterministic terms are indicated in bold type.

Table 4: Estimates of d based on a semiparametric Whittle method

	15	20	21	22	23	25	30
Gold	**1.039**	**1.154**	**1.177**	1.220	1.240	1.285	1.301
Silver	**0.879**	**1.012**	**1.020**	**1.052**	**1.081**	**1.021**	**0.976**
Palladium	0.514	0.777	0.791	**0.834**	0.808	0.793	**0.957**
Platinum	0.764	**0.897**	**0.885**	**0.917**	**0.949**	**0.912**	**0.908**
Rhodium	**0.848**	**1.008**	**0.906**	**0.888**	**0.931**	**0.925**	**1.023**
I(1) Low	0.787	0.816	0.820	0.824	0.828	0.835	0.849
I(1) High	1.212	1.184	1.179	1.175	1.171	1.165	1.150

Note: Evidence of unit roots at the 5% level is indicated in bold type

Table 5: Estimates in the context of breaks with white noise disturbances

		d	Intercept	A linear trend
GOLD	1972m1 – 1980m4	1.26 (1.08, 1.58)	3.803 (53.65)	-----
	1980m5 – 2001m3	1.06 (0.96, 1.19)	6.233 (255.29)	-----
	2001m4 – 2013m12	1.06 (0.96, 1.19)	5.551 (138.82)	0.0098 (2.301)
SILVER	1972m1 – 1980m4	1.28 (1.00, 1.72)	4.973 (45.78)	-----
	1980m5 – 2001m8	1.06 (0.96, 1.18)	7.132 (107.26)	-----
	2001m9 – 2013m12	1.14 (1.01, 1.32)	6.073 (81.52)	-----
PALLADIUM	1972m1 – 2013m12	1.09 (1.03, 1.16)	3.532 (35.98)	-----
PLATINUM	1972m1 – 1980m12	1.10 (0.96, 1.33)	4.637 (58.52)	-----
	1981m1 – 1999m7	1.03 (0.93, 1.15)	6.242 (113.85)	-----
	1999m8 – 2007m10	1.05 (0.92, 1.22)	5.824 (131.11)	0.0125 (2.369)
	2007m11 – 2013m12	1.37 (1.16, 1.63)	7.238 (110.60)	-----
RHODIUM	1972m1 – 1990m8	0.94 (0.86, 1.03)	5.257 (36.54)	0.0137 (1.990)
	1990m9 – 2013m12	1.14 (0.70, 1.23)	8.589 (59.78)	-----

Note: Values in parenthesis are the 95% confidence intervals.

Table 6: Estimates in the context of breaks with Bloomfield-type disturbances

.		d	Intercept	A linear trend
GOLD	1972m1 – 1980m4	0.78 (0.62, 0.99)	3.826 (58.61)	0.0228 (8.334)
	1980m5 – 2001m3	0.85 (0.72, 1.03)	6.267 (160.33)	-0.0027 (-2.25)
	2001m4 – 2013m12	0.96 (0.78, 1.18)	5.553 (138.94)	0.0104 (4.441)
SILVER	1972m1 – 1980m4	0.68 (0.51, 0.92)	4.971 (50.48)	0.0237 (7.948)
	1980m5 – 2001m8	0.91 (0.75, 1.11)	7.167 (108.56)	-0.0043 (1.655)
	2001m9 – 2013m12	0.83 (0.61, 1.07)	6.060 (84.32)	0.0117 (4.177)
PALLADIUM	1972m1 – 2013m12	1.10 (0.98, 1.24)	3.527 (37.77)	0.00665 (2.11)
PLATINUM	1972m1 – 1980m12	0.82 (0.69, 0.98)	4.623 (6.104)	0.0162 (4.645)
	1981m1 – 1999m7	0.89 (0.75, 1.07)	6.223 (115.08)	-----
	1999m8 – 2007m10	0.94 (0.70, 1.32)	5.824 (131.24)	0.0125 (3.771)
	2007m11 – 2013m12	0.94 (0.48, 1.68)	7.256 (104.21)	-----
RHODIUM	1972m1 – 2013m12	1.14 (1.03, 1.27)	5.269 (36.46)	0.00298 (2.401)

Note: Values in parenthesis are the 95% confidence intervals.

Figure 3: :Log-prices of gold and its estimated trend

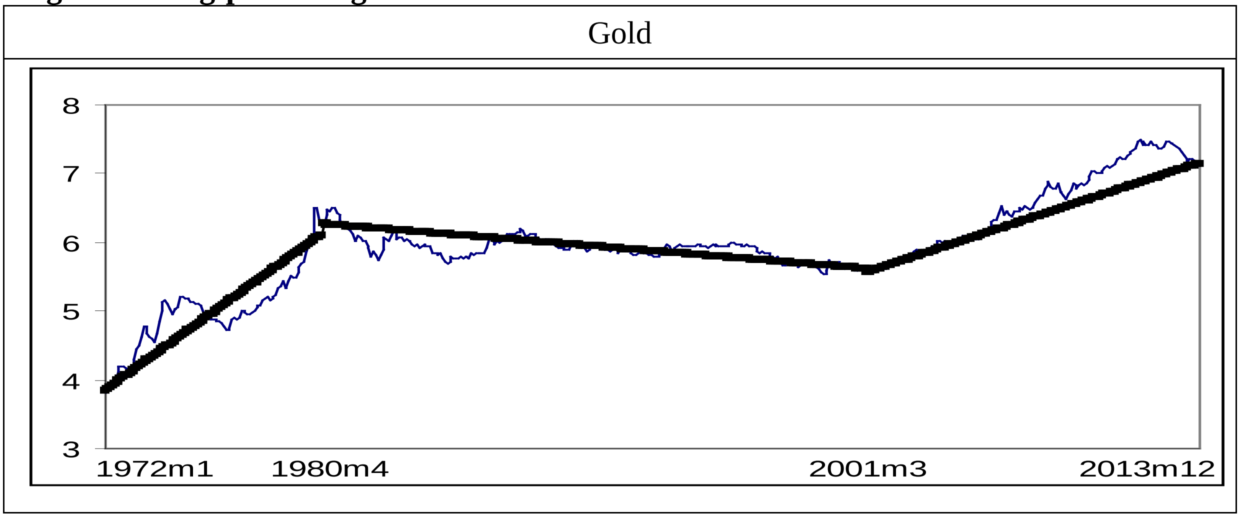

Figure 4: :Log-prices of silver and its estimated trend

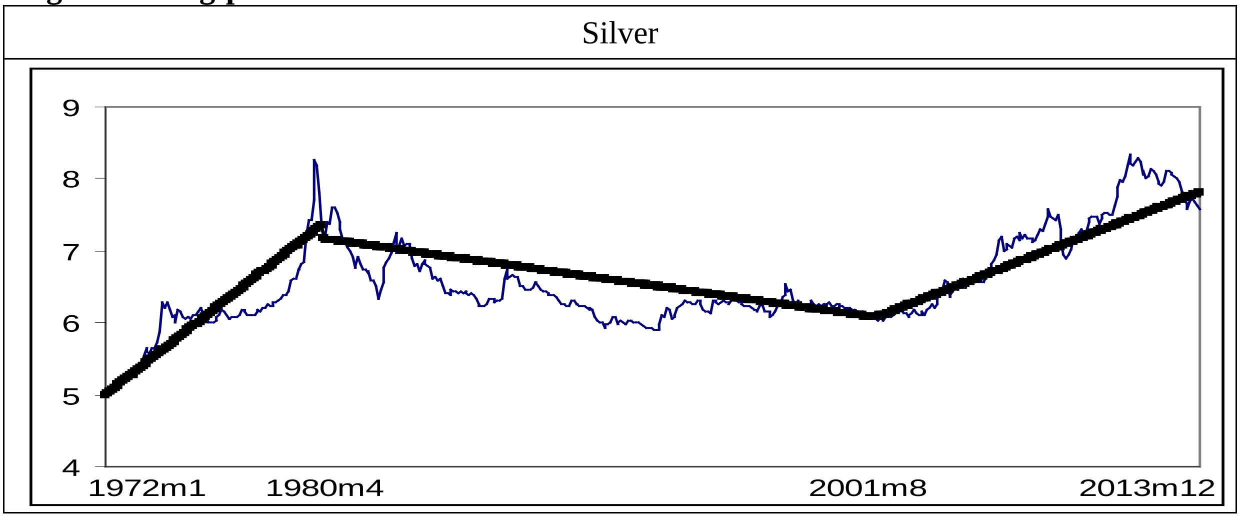

Figure 5: :Log-prices of palladium and its estimated trend

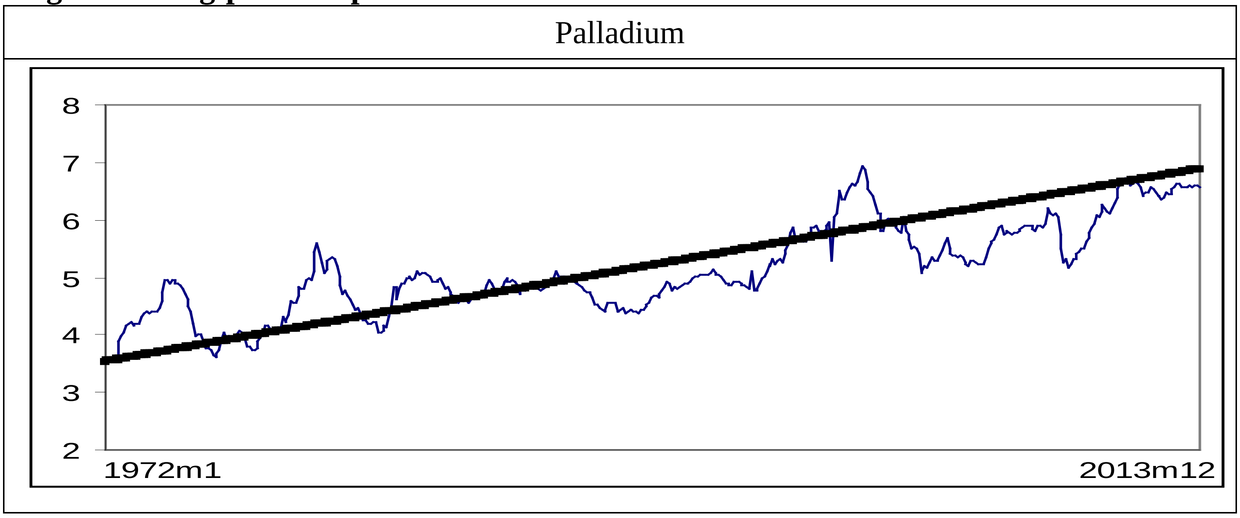

Figure 6: :Log-prices of platinum and its estimated trend

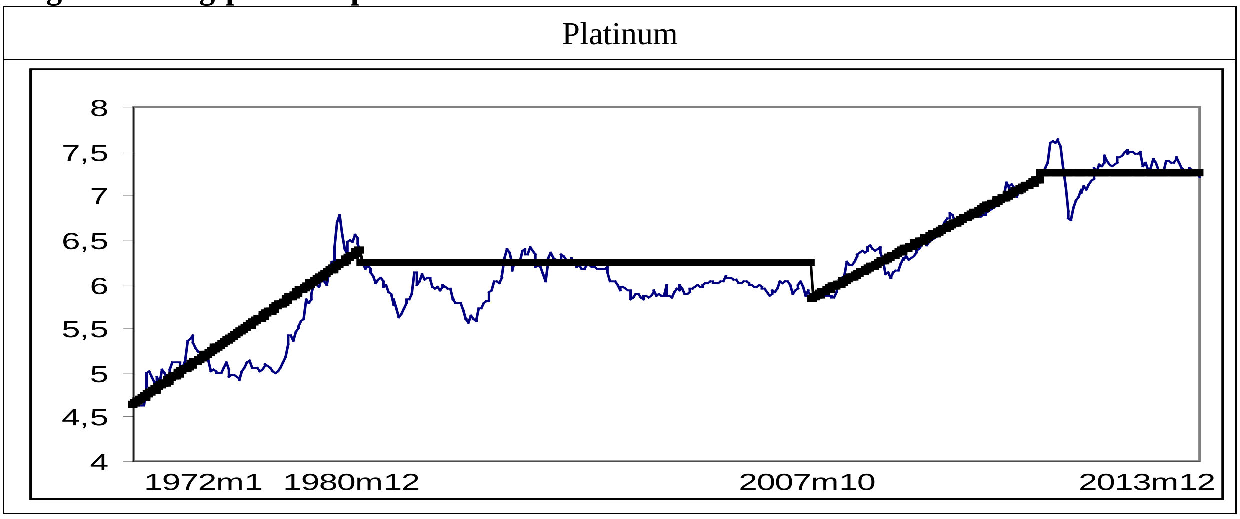

Figure 7: :Log-prices of rhodium and its estimated trend