

Return Spillovers Between White Precious Metal ETFs: The Role of Oil, Gold, and Global Equity

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Abstract

This paper investigates the relationship between white precious metals and gold, oil and global equity by means of spillovers and volatility transmission. Relying on the recently introduced ETFs, this study is the first to analyse return spillovers derived from an E-GARCH model and to take into account frequency dynamics to understand changes in connectedness across periods of time. Results uncover numerous channels of return transmission across the selected ETF markets over the last 10 years and highlight the role of gold ETFs as the most influential market in the sample. Furthermore, our work provides insights into the characteristics of white precious metal markets using a hidden semi-Markov model. Finally, we argue that even though silver and platinum have gained more importance as investment assets over the last few years, palladium still very much remains an industrial metal.

Keywords: Precious Metals, Oil, Spillovers, Volatility Transmission

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1. Introduction

Silver, platinum and palladium have traditionally been viewed as precious metals used for production purposes rather than as investment vehicles. Recently however, white precious metals have received increased attention from investors due to the introduction of new Exchange Traded Funds (ETFs). Figures 1 to 4 show the increasing importance of investment demand for the four major precious metals over time.

Insert Figures 1 to 4 about here

Being relatively new asset classes (data for palladium and platinum ETFs is only available from the 1st of August 2010 onward), the problem of interconnectedness between white metal markets is still somehow unexplored in academic literature. This paper fills a gap by investigating the dynamic linkages between silver, platinum and palladium ETFs, as well as other significant asset classes, such as gold, oil and global equities.

More precisely, we test how gold, oil and global equity markets affect the behaviour of white metal markets. There are many reasons to believe that linkages between these target markets should exist. Gold and silver are somewhat close substitutes because of their use in jewellery production, their role as a monetary reserve and their active use in industrial production. Therefore, a high correlation and information transmission between these two markets can be expected. However, an empirical answer to the matter has still not been delivered by fellow researchers. Lucey and Tully (2006) and Sari et al. (2010) for example show that the long-run impact of gold returns on silver is quite important, where the latter example shows that gold explains 16% of the variation of silver returns, 10% of the variation of platinum returns and 7% of the variation of palladium returns. Furthermore, this relationship is also observed the other way around: white metal returns transmit information to each other and to gold. On the other hand, Balcilar et al. (2015) find that by taking different regimes into account, the effect of

the gold price on silver can be as high as 17 times greater than the effect of the silver price on gold.

The relationship between oil and gold is well-evidenced in literature. Baffes (2007) argues that a rise in the price of oil by 1\$ results in an increase of 0.34\$ in the price of gold and an increase of 0.50\$ in the price of silver. O'Connor et al. (2015) summarise the relevant literature by arguing that oil drives inflation and inflation drives gold.

The importance of global equity price movements for the price of gold has been demonstrated by Baur and Lucey (2010) and Baur and McDermott (2010), both proving that gold has safe haven qualities during market turmoils. The hedging potential of white precious metals against equity prices has also been studied over the past few years. Hillier et al. (2006) consider the time period between 1976 and 2004 and find that silver has a hedging potential during high volatility periods, but that this ability is more pronounced for gold and platinum. Differentiating between bullish and bearish environments, Belousova and Dorfleitner (2012) argue that adding silver to a portfolio during bullish periods reduces volatility and enhances returns, while during bear markets, platinum is shown to lose its diversification properties.

Our study augments the existing literature in several ways. First, this paper examines the time-frequency dynamics of connectedness for gold, silver, platinum, palladium, oil and global equity ETFs using the new variance decomposition methodology proposed by Barunik and Krehlik (2015). Therefore, we discuss new stylized facts about cyclical properties of transmission mechanism in the precious metals markets and examine the time-frame of connectedness. Second, we provide valuable insights to white precious metal investors by running an E-GARCH model in order to quantify the impacts of daily returns of oil, gold and equity on the return of silver, platinum and palladium. Finally, we use the Hidden semi-Markov model (HSMM) to provide novel evidence on the return characteristics of white metal ETF

markets.

The remainder of this paper is organised as follows: section 2 discusses the relevant academic literature, sections 3 and 4 shed light on data and the methodology while sections 5 and 6 present and discuss the results. A conclusion of the paper is provided in section 7.

2. Literature Review

White precious metals gained increased attraction as investment vehicles over the past few years. Recent findings point towards the impossibility to consider precious metals as a single asset class due to the distinct differences between them (Batten et al. (2010)) with gold having unique characteristics. It is not surprising that the relationship between gold and white precious metals has been the subject of research over the past few years. Early on, Chan and Mountain (1988) and Ma and Soenen (1988) argue for the existence of a long-run relationship between gold and silver. A break in the relationship between the two metals is found to have occurred during the 1990's (Ciner (2001)) even though a positive long-run relationship persisted over time (Lucey and Tully (2006)). Regarding gold's relationship with platinum, Kearney and Lombra (2009) find the relationship to be negative, even though an empirical result can not be drawn as the relationship between gold and platinum was time-varying between 1985 and 2006 - the time-window considered in the study. Chng and Foster (2012) rely on a VAR framework consisting of all four precious metals and find evidence for a significant effect of the convenience yields of gold and silver on platinum and palladium returns. Considering the similarity of the four precious metals, which are all important for industry but also considered financial investment vehicles, a relationship between them should exist and including gold in this study is therefore vitally important when trying to understand pricing patterns of white precious metals.

Oil is probably the most important resource used in industry and there-

fore considered to be a signal of future industrial production activity. If industrial activity increases, the demand for oil would rise and with it the oil price. In the light of precious metals as production input, an increase in industrial production will lead to an increased demand for precious metals and will therefore have a positive effect on their price. Considering precious metals as investment vehicles, O'Connor et al. (2015) argue that oil drives inflation which in turn drives the price of gold. In the light of white precious metals as investment substitutes of gold, the same effect should be observable for silver, platinum and palladium. Conciliating both arguments, a rising oil price positively influences the investment and industrial demand of precious metals. Indeed, Adrangi et al. (2003) find evidence for a positive relationship between silver and both the US Consumer Price Index and the American Industrial Production Index. Recently however, Bampinas and Panagiotidis (2015) argues that the positive relationship between silver and US inflation is a modern phenomenon since a long-run positive relationship can't be observed between 1791 and 2010. Results somewhat conflicting with Taylor (1998), who finds that silver was a hedge against inflation between 1914 and 1996. Working with recent data from 1976 to 2004, Hillier et al. (2006) find evidence for silver's and platinum's positive relationship with inflation. Following the argumentation that money supply is the very root of inflation (Artigas (2010)), Batten et al. (2010) provide evidence for the importance that monetary variables have on palladium. Focusing on the direct link between oil and white precious metals, and not via the detour of inflation, Soytaş et al. (2009) focus their research on the Turkish economy and find evidence for a positive relationship between oil price shocks and the price of silver, pointing towards the industrial importance of silver in the Turkish economy. Jain and Ghosh (2013) observe similar results for the Indian economy and augment the research by looking at platinum. A noteworthy argumentation of the authors is that price increases of precious metals occur because of price increases in oil, again channeled through inflation. It

seems however, that the relationship between oil and silver seems to disappear on a more global level (Bhar and Hammoudeh (2011)), though Bildirici and Türkmen (2015) take into account a larger time window of observations and indeed finds evidence for a long-run cointegration between global silver and oil prices: indicating that the relationship might be time-varying. In a recent study that takes into account daily prices of silver, platinum and palladium between July 1993 and January 2014, Behmiri and Manera (2015) conclude that negative oil price shocks do not affect the volatility of silver, while positive oil price shocks decrease the volatility of silver prices. Results are slightly different for platinum, where negative oil price shocks increase volatility while positive oil price shocks have a cooling effect on the volatility of platinum prices. Regarding palladium, any oil price shock, whether positive or negative, increases the volatility of palladium prices, pointing towards the industrial importance of the metal.

The relationship between precious metals and equity prices has to be understood in the light of the possible hedging and safe haven potential of the metals, akin to their properties as investment assets. Hillier et al. (2006) indeed prove that gold, silver and platinum offer diversifying benefits when added to a portfolio of US and international stocks, results supported by Conover et al. (2009). Belousova and Dorfleitner (2012) differentiate between bull and bear markets and strengthen the attractiveness of silver as an investment asset because it reduces portfolio volatility and enhances returns during bull markets, while reducing portfolio risk during bear markets. Platinum and palladium lower portfolio volatility in bull markets but these diversification benefits seem to vanish away in bear markets. The benefits of platinum and palladium are questionable when added to European portfolios. Sarafrazi et al. (2014) indeed argue that gold and silver seem to be the only precious metals that offer diversification benefits against a variety of European stock and bond portfolios. Recently, Lucey and Li (2015) took the discussion a step further and looked at the safe haven implications of

white precious metals against the S&P 500 and US 10 year bonds. Results show that platinum and palladium acted as safe havens against falling US equity prices more often than silver did.

Volatility spillovers between precious metals was studied by Batten et al. (2010) and linked to fluctuations in debt, equity, monetary and financial variables. Results indicate an important effect of financial variables on platinum and palladium but not on silver. It seems that silver is a case apart, where the price volatility is a function of the volatility of the other precious metals. Empirically however, between 1986 and 2006, the volatility of the four precious metals were influenced by each others volatility, highlighting the interdependence of the different metals. Batten et al. (2015) go a step further into the investigation of return spillovers amongst precious metals and find that while gold and silver show consistency in the spillovers between each other, platinum and palladium are separated from the two, even separated from themselves. Results in favour of silver's close relationship to gold due to it's attractiveness as a financial investment. Morales and Andreosso-O'Callaghan (2011) look at the time window between 1995 and 2007 to understand the effects of the Asian crisis and the Global Financial crisis on volatility spillovers amongst precious metals. In line with Batten et al. (2010) clear evidence for volatility persistence between the four precious metals is observed, but it seems that gold, not silver, is the case apart since other metals do not influence the price of gold. Adding oil into their analysis, Antonakakis and Kizys (2015) model a Forecast Error Variance Decomposition (FEVD) framework consisting of the four precious metals, oil and exchange rates and find that gold, silver and platinum are net transmitters of returns and volatility spillovers, while palladium and oil are net receivers - results in contrast with Batten et al. (2015) where silver is a net receiver of volatility spillovers. Balcilar et al. (2015) propose to differentiate between high and low volatility regimes and conclude that gold is the most informative commodity in high volatility regimes while gold, platinum and

palladium are the most informative commodities in low volatility regimes - results questioning the importance of silver in a spillover model.

3. Data and Preliminary Data Analysis

This paper employs daily ETF prices of gold, silver, platinum palladium, oil and global equity², between the 19th of June 2006 and the 18th of June 2016. However, the earliest data available for platinum and palladium is from the 1st of August 2010. Daily returns are defined as:

$$R(t) = \ln(P_t) - \ln(P_{t-1}) \quad (1)$$

where $\ln(P_t)$ is the natural logarithm of the closing price at date t and $\ln(P_{t-1})$ is the natural logarithm of the closing price at date $t - 1$. The conditional distribution that produces a sequence of observations with length d can be specified as:

$$\mathbb{P}_{i,d}(\mathbf{X}_{t+1:t+d}) = \mathbb{P}(\mathbf{X}_{t+1:t+d} | \mathbf{S}_{t+1:t+d} = i) \quad (2)$$

where i represents one of the states (i.e. $i \in \{1, 2, \dots, m\}$), $\mathbf{X}_{t+1:t+d}$ denotes the sequence of observations from time $t + 1$ to $t + d$, and $\mathbf{S}_{t+1:t+d}$ indicates the sequence of states starting at time $t + 1$ and ending at $t + d$. Therefore, state i beginning at $t + 1$ produces a sequence of d observations. Details on the distribution of return series are discussed in section 4.4.

There are 2,518 ETF observations of silver, gold, oil and global equity, and 1,623 observations for platinum and palladium ETFs. Summary statistics of price returns in the six ETF markets can be found in Table 1, where sample means, medians, maximums, minimums, standard deviations, skewness, kurtosis, and the Jarque-Bera (JB) statistic are reported. The JB

²The data was downloaded from www.etfdb.com. The following six ETFs are included in our analysis: iShares Silver Trust (SLV), ETFS Physical Platinum (PPLT), ETFS Physical Palladium (PALL), SPDR Gold Trust (GLD), United States Oil Fund (USO), Vanguard Total Stock Market ETF (VTI).

Statistics indicate a departure from normality and the existence of nonlinear components in the data generating process.

Insert Table 1 about here

Table 2 reports the unit root test results, where various tests reject the null hypothesis of a unit root at the 0.01 significance level. It can therefore be concluded that the price return series are stationary.

Insert Table 2 about here

4. Methodology

4.1. Regime-switch cointegration test

The regime-switch cointegration technique of Gregory and Hansen (1996) are conducted to test for market integration as the sample may contain time-varying elements and structural breaks. Hatemi-J (2008) further develops a model that incorporates the impact of two structural breaks on both the intercept and the slope (i.e. two regime shifts). The model used in this study could be specified in the bivariate case as:

$$y_{1t} = \mu_1 + \mu_2 D_{1t} + \mu_3 D_{2t} + \lambda_1^T y_{2t} + \lambda_2^T y_{2t} D_{1t} + \lambda_3^T y_{2t} D_{2t} + \varepsilon_t \quad (3)$$

where D_{1t} and D_{2t} are dummy variables defined as:

$$D_{1t} = \begin{cases} 0, & \text{if } t \leq [n\tau_1] \\ 1, & \text{if } t > [n\tau_1] \end{cases} \quad (4)$$

and

$$D_{2t} = \begin{cases} 0, & \text{if } t \leq [n\tau_2] \\ 1, & \text{if } t > [n\tau_2] \end{cases} \quad (5)$$

The date of pairwise breaks is estimated with the unknown parameters $\tau_1 \in (0, 1)$ and $\tau_2 \in (0, 1)$. The null hypothesis of no cointegration between markets is tested by the Z_t statistic of Phillips (1987). The Z_t statistic is estimated as $Z_t^* = in \int_{(\tau_1 \tau_2) \in T} Z_{t((\tau_1 \tau_2))}$, where $T = (o.15n, 0.85n)$.

4.2. E-GARCH

An E-GARCH model is used to estimate the impacts of daily returns of gold, oil and equity on the return of white precious metals. The specification of the conditional variance equation ensures that the conditional variance is strictly positive, and therefore releases the non-negative constraints of a simple GARCH model. On the other hand, the conditional variance specification allows asymmetric innovations of bad news in a way that it generates higher volatility than good news. The mean equation can be modelled as:

$$R_t = \delta_0 + \sum_i^p \lambda_i R_{t-i} + \delta_1 GLD_t + \delta_2 USO_t + \delta_3 VTI_t + v_t \quad (6)$$

where R_t is the daily return of white precious metal ETFs, the notations GLD , USO and VTI represent gold, oil and global equity respectively. The variance equation in equation 7 is specified such that an E-GARCH (1,1) specification can be written as:

$$\ln(h_t) = \omega + \sum_{i=1}^p \alpha_i \left| \frac{v_{t-1}}{h_{t-1}^2} \right| + \sum_{k=1}^r \gamma_k \frac{v_{t-k}}{h_{t-k}^2} + \sum_{j=1}^q \beta h_{t-j} \quad (7)$$

where ω is the intercept, h_t denotes the conditional volatility, v_{t-1} represents the innovation term in period $t - i$, and γ_k captures asymmetric captures asymmetric positive and negative shocks. The presence of the asymmetric leverage effect is indicated with the term $\gamma_k \neq 0$.

4.3. Frequency Dynamics of Connectedness

We employ the methodology suggested by Barunik and Krehlik (2015) to measure the dynamics and intensity of ETF return spillovers across the above mentioned asset classes, taking frequency dynamics into account. Diebold and Yilmaz (2012) adopt the generalised variance decomposition methodology of Pesaran and Shin (1998) to obtain directional connectedness. Barunik and Krehlik (2015) in turn apply spectral representations of variance decomposition locally to retrieve time-frequency (Stiassny (1996)).

This frequency domain analysis enables us to analyse long-run, medium-run, or short-run connectedness using frequency dependent connectedness measures. While Diebold and Yilmaz (2012) employ a VAR model, Barunik and Krehlik (2015) adopt the spectral method of Stiasny (1996) and Dew-becker and Giglio (2016) to measure unconditional connectedness relations in frequency domain. The following frequency response function can be used to decompose the generalised impulse response function - consider the spectral behaviour of series X_t as:

$$S_x(\omega) = \sum_{h=0}^{\infty} E(X_t X_{t-h}) e^{-ih\omega} = \Psi(e^{-ih\omega}) \sum \Psi(e^{ih\omega}) \quad (8)$$

where ω is the frequency, ∞ implies infinite horizon relations in the setting and $\Psi(e^{-ih\omega}) = \sum_{h=0}^{\infty} \Psi_h e^{-ih\omega}$ (Barunik and Krehlik (2015)). The unconditional generalised forecast error variance decomposition (GFEVD) on a particular frequency ω is specified as:

$$(\Theta(\omega))_{i,j} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{\infty} (\Psi(e^{-ih\omega}) \sum)_{i,j}^2}{\sum_{h=0}^{\infty} (\Psi(e^{-ih\omega}) \sum \Psi(e^{ih\omega}))_{i,i}} \quad (9)$$

where 9 can be standardised as:

$$(\tilde{\Theta}(\omega))_{i,j} = \frac{(\Theta(\omega))_{i,j}}{\sum_{j=1}^k (\Theta(\omega))_{i,j}} \quad (10)$$

The accumulative connectedness table (i.e. specified over an informative frequency band) proposed by Barunik and Krehlik (2015) over an arbitrary frequency band $d = (a; b)$ can be expressed as:

$$(\tilde{\Theta}_d)_{i,j} = \int_a^b (\tilde{\Theta}(\omega))_{i,j} d\omega \quad (11)$$

Therefore the overall connectedness within the frequency band d can be defined as:

$$C^d = \frac{\sum_{i=1, i \neq j}^k (\tilde{\Theta}_d)_{i,j}}{\sum_{i,j} (\tilde{\Theta}_d)_{i,j}} = 1 - \frac{\sum_{i=1}^k (\tilde{\Theta}_d)_{i,i}}{\sum_{i,j} (\tilde{\Theta}_d)_{i,j}} \quad (12)$$

It is important to note that C^d close to unity implies strong connections within the spectral band ($d = (a; b)$) while the aggregate connectedness

amongst the variables could be low. We are interested in measuring the contribution of one market ($i \neq j$) to another market i , which can be defined as *within from* connectedness on the spectral band d :

$$C_{i\leftarrow}^d = \sum_{j=1, i \neq j}^k (\tilde{\Theta}_d)_{i,j} \quad (13)$$

In the same way, we can measure the variance from market i to another market as the *within to* connectedness on the spectral band d :

$$C_{i\rightarrow}^d = \sum_{j=1, i \neq j}^k (\tilde{\Theta}_d)_{j,i} \quad (14)$$

Another measure is used to quantify the difference between variance received and variance given from an asset. This *within net* connectedness is defined as:

$$C_{i,net}^d = C_{i\rightarrow}^d - C_{i\leftarrow}^d. \quad (15)$$

If $C_{i,net}^d$ is positive, it indicates that the variable i transmits more information than it receives from the other variables in a stable VAR system. The pairwise connectedness *between* market i and j can be specified as:

$$C_{i,j}^d = (\tilde{\Theta}_d)_{j,i} - (\tilde{\Theta}_d)_{i,j} \quad (16)$$

The contribution of a particular frequency band d to the aggregate measure has to be weighted. Barunik and Krehlik (2015) show that the aggregate measure on the frequency band d is specified as:

$$\tilde{C}^d = C^d \cdot \Gamma(d) \quad (17)$$

Where the spectral weight $\Gamma(d) = \frac{\sum_{i,j=1}^k (\tilde{\Theta}_d)_{i,j}}{\sum_{i,j} (\Theta)_{i,j}} = \frac{\sum_{i,j=1}^k (\tilde{\Theta}_d)_{i,j}}{k}$ is the contribution of frequency band d to the whole VAR system and C^d is the total connectedness measure on the connectedness tables $(\tilde{\Theta}_d)$ corresponding to an arbitrary frequency of band d . The total connectedness measures C can be obtained by $S^g(H) = \sum_d \tilde{C}^d$ (Diebold and Yilmaz (2012)).

The time-frequency dynamics of connectedness for ETF markets can be obtained by using the spectral representations of variance with a moving window of 250 trading days. A lag length of two is used to capture the dynamics in the window; the results for time-frequency decomposition of return connectedness is shown in Table 7. The frequency bounds for daily data should be interpreted in cycles, with a classical spectrum between 0 and $\frac{\pi}{2}$. Since we work with daily data, the highest possible frequency is 0.5 cycles per day, which amounts to 2 days. We investigate the dynamics for 1 to 5 days, 5 to 20 days, 20 to 60 days, and 60 to 250 days (in other words weekly, monthly, quarterly and yearly cycles). The H steps forecast horizon is set to be 100 which is a common approximation in literature.

4.4. Hidden Semi-Markov Model

A hidden semi-Markov model (HSMM) is used to analyse return characteristics of the white precious metal ETF market. Figure 5 shows the structure of the HSMM. The model can be decomposed into two processes: the unobservable state process ($\mathbf{S}_{1:T} = s_1, s_2, \dots, s_T$) and the observation process ($\mathbf{X}_{1:T} = x_1, x_2, \dots, x_T$). The sojourn time of each process follows a sojourn time distribution which can be defined as:

$$d_i(u) = \mathbb{P}(s_{t+u+1} \neq j, \mathbf{s}_{t+1:t+u} = j | s_{t+1} = j, s_t \neq j) \quad (18)$$

The state transition probability of the data generating process can be defined as:

$$\gamma_{(i,d)(j,d')} = \mathbb{P}(\mathbf{S}_{t+1:t+d'} = j | \mathbf{S}_{t-d-1:t} = i) \\ \text{where } i \neq j, \quad i, j \in \{1, 2, \dots, m\} \quad (19)$$

Specifically, the system stays in state i for d periods from $t - d + 1$ to t and then transits to state j for d' periods from $t + 1$ to $t + d'$. Note that $\gamma_{(i,d)(i,d')} = 0$ since the sojourn time is controlled by the sojourn time distribution in the HSMM. The transition probability matrix (TPM) for the

HSMM can be specified as:

$$\Gamma = \begin{pmatrix} 0 & \gamma_{(1,d_1)(2,d_2)} & \cdots & \gamma_{(1,d_1)(m,d_m)} \\ \gamma_{(2,d_2)(1,d_1)} & 0 & \cdots & \gamma_{(2,d_2)(m,d_m)} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{(m,d_m)(1,d_1)} & \gamma_{(m,d_m)(2,d_2)} & \cdots & 0 \end{pmatrix} \quad (20)$$

We follow Bulla and Bulla (2006) and apply the right-censored type HSMM because the assumption is more realistic for our ETF data. We set the conditional distribution as normal distribution and sojourn time distribution as negative binomial distribution in this study as it fits our data well. We use the expectation-maximisation algorithm to estimate the model and the Viterbi algorithm to globally decode the sequence of states.

Insert Figure 5 about here

5. Empirical Results

5.1. Cointegration

Table 3 reports the relationship between the three white precious metals (i.e. silver, platinum and palladium) and other asset classes (i.e. gold, oil and global equity). The results show that all markets are well integrated while break dates can be identified around the years 2011, 2012, 2013, and 2014.

Insert Table 3 about here

The results on the relationship between gold and silver prices are mixed in the literature. Ciner (2001) does not observe a long-run relationship between gold and silver prices and concludes that the two markets are rather segmented. This conclusion however is based only on the conventional cointegration test of Johansen (1991) and is inconsistent with other studies (see for example Wahab et al. (1994), Escibano and Granger (1998) or Adrangi

and Chatrath (2002)). This inconsistency is raised because of the fact that the standard cointegration tests for the null hypothesis of no-cointegration can have substantially reduced power and hence lead to erroneous conclusions (see Gregory and Hansen (1996) for more details). Overall, our approach confirmed the presence of cointegration between all nine commodity pairs: silver-gold, silver-oil, silver-equity, platinum-gold, platinum-oil, platinum-equity, palladium-gold, palladium-oil, and finally, palladium-equity.

5.2. E-GARCH Spillover effects

Tables 4 to 6 present the parameters of the univariate E-GARCH(1,1) model for each white metal ETF market. Panel A of each table shows the estimated coefficients, standard errors, z-statistics and p-values for the conditional mean equation as in equation 6. All three white precious metals exhibit a significant own mean spillover from their first lagged returns. In all cases, the mean spillovers are positive, results in line with the literature on other financial assets in the field. Table 4 presents the empirical results of return spillover from other asset classes to silver ETFs: there is a positive and significant relationship between the mean return in the silver market and the return in the gold market. In particular, a 1% increase of daily returns in the gold market leads to an increase of 1.2813% of daily silver returns. The response of the silver price to a 1% increase in oil ETFs is 0.2685% and 0.0788% to global equity. The response of silver to a 1% oil price increase is therefore much lower than the results obtained by other studies. Baffes (2007) finds that a 1\$ increase of the oil price leads to a 0.50\$ increase of the silver price, while Bildirici and Türkmen (2015) finds evidence for a 1.33% increase of the price of silver in response to a 1% increase of the price of oil. Results pointing towards the shift of silver from an industrial to an investment asset.

Insert Table 4 about here

Table 5 presents the empirical results for platinum ETFs: we find evidence for a positive and significant relationship between the mean return in the platinum market and returns in the gold market. More specifically, a 1% increase of daily returns in the gold market leads to a 0.73% increase of daily returns in the silver market. The response of platinum to a 1% increase in oil ETFs is 0.2538%, and 0.0723% to global equity.

Insert Table 5 about here

Table 6 presents the results for palladium, again, a positive and significant relationship between the mean return in the platinum and the gold market is observed. The effect of the gold market on palladium ETFs is that a 1% change in gold market returns lead to an increase of 0.6525% in the price of palladium ETFs. The response of palladium ETFs to a 1% increase in the price of oil is 0.555% and 0.16078% for global equity. Furthermore, we can detect the presence of an asymmetric leverage effect indicated by the term $\gamma_k \neq 0$.

Insert Table 6 about here

5.3. Frequency Dynamics of Connectedness

Table 7 displays the decomposition of time-frequency dynamics of connections. The largest portion of connections is created from the higher frequency of one week up to one month (top panel of Table 7), with a value of 43.181%. The connectedness of monthly, quarterly, and yearly cycles is 7.963%, 2.29%, and 0.573% respectively. Considering the time dynamics of frequency connections, an interesting observation is that higher frequency bands dominate lower frequency bands. In particular, connectedness has been driven mostly by information up to one week. The result is consistent with the recent study of Barunik et al. (2013) in which the authors argue for the empirical importance of frequency sources of connectedness as shocks to volatility may have different implications on uncertainty. An example

being mining costs, where uncertainty may reveal fundamental changes in investor's future price expectation, while the influence of this long-run or fundamental impact may be different to short-run source of uncertainty.

Table 7 also displays the net-spillover indices for individual ETF markets. The weekly contribution of the silver market to other markets is 71.634%, furthermore, silver contributes 30.559% of the spillover index to gold as a close substitute. In contrast, oil only transmits 12.725% to other ETF markets. Gold receives 56.294%, the most spillovers from other markets, making it the largest net-recipient of price spillovers. To summarise, silver, palladium and equity are net-contributors to the spillover index, while gold, oil and platinum are net-recipients.

Insert Table 7 about here

Figures 6 to 14 illustrate the time-frequency dynamics of connectedness for silver, platinum, palladium and other markets. The decomposition of the bi-directional connectedness of frequency bands between 1 and 5 days are denoted by the red line, between 5 and 20 days are denoted by the black line, between 20 and 60 days are denoted by the blue line, and between 60 and 120 days are denoted by the green line. Several interesting observations can be made. The gold-silver market maintains the highest spillover index as expected, but the connectedness is decreasing since August 2013. The smallest connectedness is between gold and palladium. Regarding equity, the equity-silver market exhibits the highest spillover index, while the connectedness is recently decreasing since March 2014; the smallest connectedness is found for platinum. Regarding oil, the oil-palladium market is found to have the highest spillover-index, underlining the industrial importance of the metal.

Insert Figures 6 to 14 about here

5.4. Hidden Semi-Markov Model Results

Table 8 displays the estimated parameters of the fitted two-state HSMM for silver, platinum, and palladium³. Considering daily returns of all three white metals ETFs, the variances of state 2 are much higher than those of state 1. Hence, state 2 corresponds to the higher volatility state, while state 1 corresponds to the low volatility state. Although the mean of state 2 for all three ETFs are negative, z-statistics indicate that the negative means of state 2 are not significantly different from zero. Therefore, there is no statistical evidence to associate high volatility with low mean of returns. Additionally, z-statistics show that the means of state 1 for silver and platinum are not significantly different from zero, while palladium on the other hand has a significantly positive mean for its low volatility state.

The average sojourn time of either state 1 or state 2 for palladium is much longer than for silver and platinum, suggesting that the volatility clustering effect in palladium is more persistent. The average sojourn time for silver is shortest among the three ETFs. Its low volatility state (avg. 17 days) lasts longer than its high volatility state (avg. 10 days). This indicates that the states of silver can frequently transits between low and high volatility states, which can be confirmed from the decoding results later on.

Insert Table 8 about here

Table 9 displays the estimated parameters of the fitted three-state HSMM. State 1, state 2 and state 3 are linked to low, medium and high volatility respectively. Regarding palladium, the Transition Probability Matrix (TPM) indicates that state 2 always occurs after state 1. The probability of state 2 to transit to state 1 is 23.25% and to state 3 is 76.75%. Furthermore, state 2 always occurs after state 3 and can be considered a "buffer zone" between the other two states. A "buffer zone" is also observed for the TPM of silver,

³The TPM for two-state HSMM is not reported because it is always a 2 by 2 matrix with diagonal entries of value 1 and offdiagonal entries of value 0.

but not for platinum. This may result from the fact that platinum does not have enough days of high volatility (only 26 days) during our sample period.

Palladium has a relatively long sojourn time for its low volatility state (avg. 169 days). In contrast, silver has a comparatively long sojourn time for its high volatility state (avg. 147 days). For platinum, its low and medium volatility states both have long sojourn times, with an average of 145 and 116 days respectively. Hence, the sojourn time of different level volatility states are quite different for the three metals.

Insert Table 9 about here

5.5. Decoding Results

Figures 15 to 17 show the global decoding results of fitted two-state HSMs for the three ETFs. The green backgrounds stand for the low volatility state (i.e. State 1) while the red background represents the high volatility state (i.e. State 2). We can observe that palladium and platinum share a large overlap of the periods of low and high volatility states. There are four remarkable periods:

1. Before 2013, palladium was in its high volatility state. Platinum went into a high volatility state from low volatility until the middle of 2011, with some short periods of high volatility states in 2010 and early of 2011. The high volatility of silver before 2013 mainly occurred between the end of 2011 and the middle of 2012.
2. In the middle of 2013, all three ETFs were in the high volatility state.
3. During 2014, all three ETFs were in the low volatility state.
4. After June 2015, both palladium and platinum went into a high volatility state, while silver remained in the low volatility state.

Insert Figures 15 to 17 about here

Figures 18 to 20 show the global decoding results of fitted three-state HSMs for the three ETFs. The purple background stands for the low

volatility state, the green background stands for the medium volatility state, and finally, the red background stands for the high volatility state. Palladium has two relatively long periods of high volatility, one before 2012 and the other around the beginning of 2016. Platinum does not have a long period of high volatility in our sample period. Its high volatility state lasted only for a few days. Platinum and palladium were both mainly in low volatility states from 2013 to the middle of 2015. We can still observe that palladium and platinum share a large overlap of the same level of volatility states. However, silver shows a different pattern since it has three long periods of high volatility states, which are in 2011, the middle of 2013, and the beginning of 2015. Additionally, its low and medium volatility states last for very short periods and transit to each other frequently.

Insert Figures 18 to 20 about here

6. Discussion of Results

Our findings indicate that gold plays an important role for silver ETFs, followed by platinum and palladium ETFs. Due to their low cost, low investment scale and their ability to track the gold price very closely (Ivanov (2013)), gold ETFs are a popular investment asset since their introduction in 2003. The strong relationship between gold and silver is supported by previous literature. Ma and Soenen (1988) find a strong relationship in both the spot and the futures markets and propose an arbitrage strategy based on that relationship. Subject to a short time window of 6 years during the 1990's, Ciner (2001) argues for the nonexistence of a long-run relationship between the two metals. Lucey and Tully (2006) support the existence of a break in the relationship during the 1990's but find that on the long-run, the relationship between gold and silver is positive. Batten et al. (2013) question a profit making strategy based on the gold-silver relationship as the two series don't immediately revert towards their long-term mean. Kearney and Lombra (2009) prove that the relationship between gold and platinum

evolved over time and ran through both positive and negative episodes, while Chng and Foster (2012) argue that the effect of the convenience yield of gold on platinum is significant. Batten et al. (2010) finds that the volatility of silver, platinum and palladium is influenced by gold, results in line with Batten et al. (2015) who find evidence for time-variation in the relationship: spillovers from gold to palladium weakened over time and vanished around 2010 and 2012. Our results indicate a persistent and strong relationship between gold and the other three precious metals and indicate that gold is a net-recipient of price spillovers; findings consistent with previous results by pointing towards a positive and significant relationship between gold and white precious metal returns.

O'Connor et al. (2015) argue that oil drives inflation, which in turn drives the price of gold. An applied example of that framework can be found in Narayan et al. (2010), where the authors argue that a 1\$ oil price increase results in an average increase of the price of gold by 0.356\$. This argumentation could be an explanation for the observed positive relationship between oil and all three white precious metals. In light of this relationship, a similar argumentation can be used for silver. Taylor (1998) and Adrangi et al. (2003) find evidence for silver's ability to function as a hedge against inflation; results rejected by Bampinas and Panagiotidis (2015) who considers 200 years of data and concludes that silver is not a long-run hedge against US inflation and only a hedge against UK inflation in a time-varying framework. Previous research somewhat support our findings: Bhar and Hammoudeh (2011) rely on different model specifications and show that no significant relationship between silver and oil can be observed, results in contrast to Jain and Ghosh (2013) who found evidence for Granger causality between oil and silver, but not between oil and platinum. Even though Charlot and Marimoutou (2014) find evidence for correlation between oil and silver/platinum, the correlation coefficient is quite small. In a recent paper and one of the few considering the effects of oil on palladium, Behmiri

and Manera (2015) find that positive oil price shocks decrease the volatility of the silver price while oil price shocks have an inverse relationship with platinum price volatility. Observations are different for palladium, where a positive oil price shock increases the volatility of palladium, underlining the industrial importance of the metal. Reboredo and Uddin (2016) continue the investigation between oil and precious metal prices and find evidence for a systematic impact of downward oil price movements on downward metal price movements. On the other hand, upwards oil price movements spill over on all precious metal prices except palladium. We add to the ongoing investigation on the relationship between oil and white precious metals by showing that the impact of oil on white precious metals is unimportant.

In academic literature, gold is considered an effective a hedging tool against equity prices. Sumner et al. (2010) consider volatility spillovers between January 1970 and April 2009 and find that no spillovers occurred from gold to US stocks, highlighting the hedging potential of gold. More formally, Baur and Lucey (2010) and Baur and McDermott (2010) show that indeed, a long-run relationship between gold and equity prices can be observed on the long-run. Sarafrazi et al. (2014) take the three studied white precious metals into account and find that silver has diversification benefits for European stock and bond portfolios. Morales and Andreosso-O'Callaghan (2014) take an international approach and indicate an insignificant relationship between silver and the Dow Jones and a significant relationship between silver and both the FTSE100 and the Nikkei225. Platinum on the other hand is found to have a significant positive relationship with the Dow Jones and the Nikkei225, but the relationship with the FTSE100 is insignificant. The formal methodology proposed by Baur and Lucey (2010) is used in Lucey and Li (2015) and applied to silver, platinum and palladium. In line with Sarafrazi et al. (2014), Lucey and Li (2015) find that on average, silver is a weaker equity hedge than gold, and that platinum and palladium have a much weaker relationship with equity prices than gold and silver. An empir-

ical answer to the nature of the relationship between white precious metals and equity prices still needs to be derived. Our results are however in line with previous findings: a relationship with equity prices was observed by means of the cointegration analysis even though the importance of equity ETFs on white metal ETFs is fairly weak.

7. Conclusion

This paper provided new empirical evidence on return spillovers between white precious metal markets from 2006 to 2016. The results improve the understanding of the impact that gold, oil and global equity has on the dynamics of the connectedness of white precious metal ETFs. This study highlighted the shift of silver and platinum from an industrial towards an investment asset, making the results not only important from a theoretical perspective, but also highly significant for a broad range of investors and practitioners. The findings can be summarised as follows.

First, the application of a regime-switch cointegration test taking into account structural breaks revealed that all market pairs (silver-gold, silver-oil, silver-equity, platinum-gold, platinum-oil, platinum-equity, palladium-gold, palladium-oil, and palladium-equity) are cointegrated.

Second, E-GARCH model results display a positive and significant relationship between the mean of returns in the gold markets and the mean of returns on silver, platinum and palladium markets - confirming the role of gold as a main source of return spillovers on white metal ETF markets. These findings are in line with previous evidence documented by Kearney and Lombra (2009), Chng and Foster (2012), Batten et al. (2010), and Batten et al. (2015) to name but a few. The results reveal that gold has a higher influence on white precious metals than oil or equity has. Indeed, we show that oil and equity have only a small effect on white precious metal prices.

Third, this paper reported new evidence on dynamic time-frequency connectedness across precious metals, oil and equity, using the approach sug-

gested by Barunik et al. (2013). The results show that higher frequency bands dominate lower frequency bands; more specifically, connectedness has been driven mostly by information up to one week. The values of net-spillover indices for individual ETF markets indicate that silver, palladium and equity are net-contributors of spillovers, while gold, oil and platinum are net-recipients. As expected, the gold-silver market pair maintains the highest spillover index, but the connectedness is decreasing since August 2013. Furthermore, the oil-palladium market is found to have the highest spillover-index, underlining the industrial importance of the metal.

Finally, estimation results of a two-state HSMM identified that the presence of volatility clustering effect in palladium is more pronounced than for both silver and platinum. Decoding the results highlighted four periods during which the high and lower volatility states of white precious metal market experienced significant changes. A three-state HSMM found that palladium has a relatively long sojourn time during its low volatility state, while silver has a comparatively long sojourn time during its high volatility state - evidence pointing towards the speculative aspects of silver. Platinum is found to have long sojourn times during both the low and medium volatility states. These findings provide useful insights into the nature of volatility of silver, platinum and palladium, and are useful for the creation of successful investment strategies or to hedge the risks of specific portfolios.

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Figure 1: Demand for Gold in Tonnes (Source: GFMS Surveys)

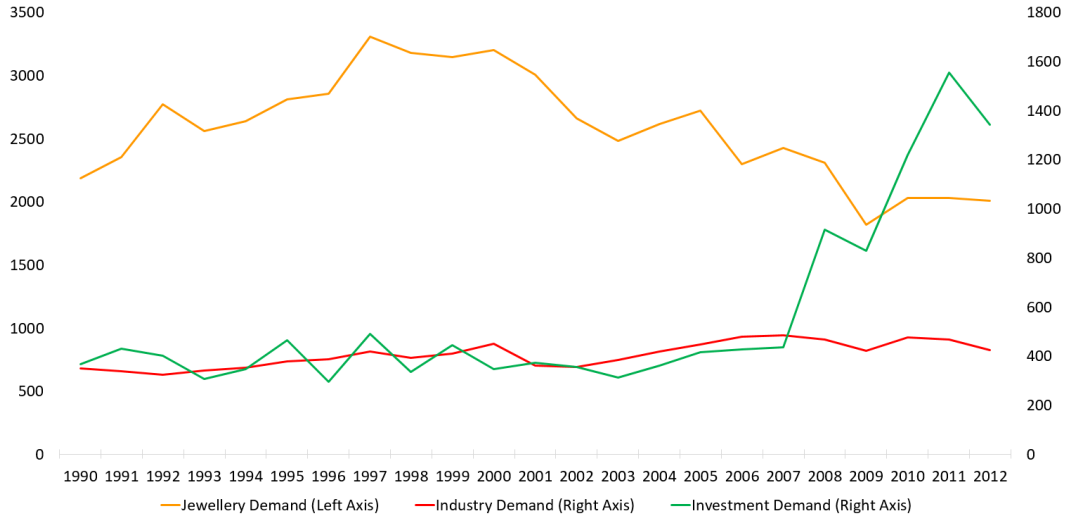


Figure 2: Demand for Silver in Million Ounces (Source: GFMS Surveys)

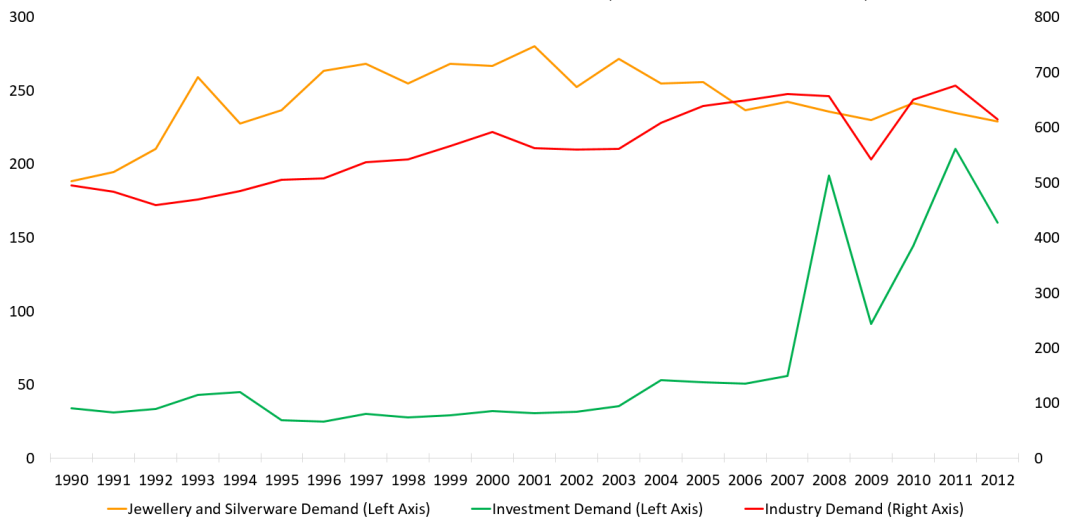


Figure 3: Demand for Platinum in Thousand Ounces (Source: Johnson Matthey)

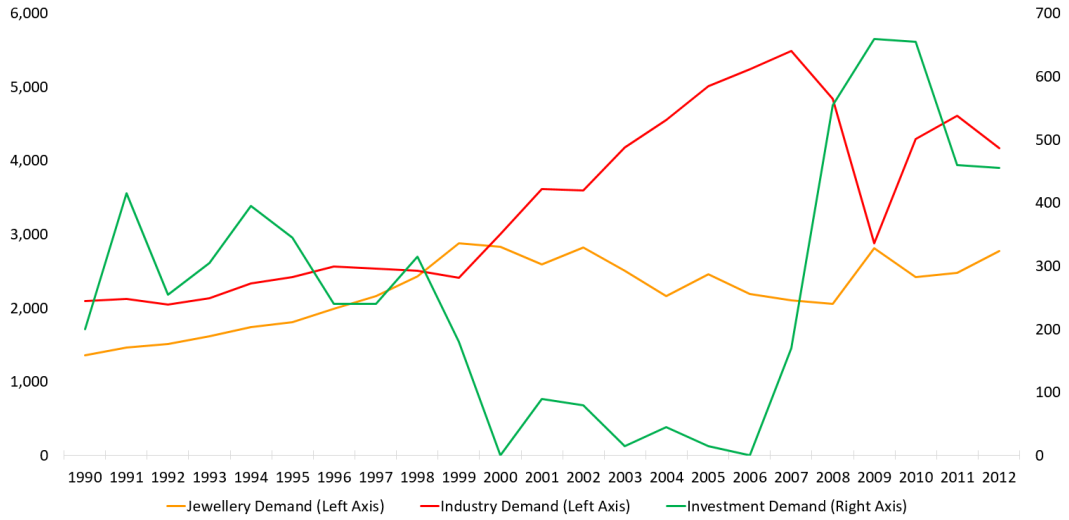


Figure 4: Demand for Palladium in Thousand Ounces (Source: Johnson Matthey)

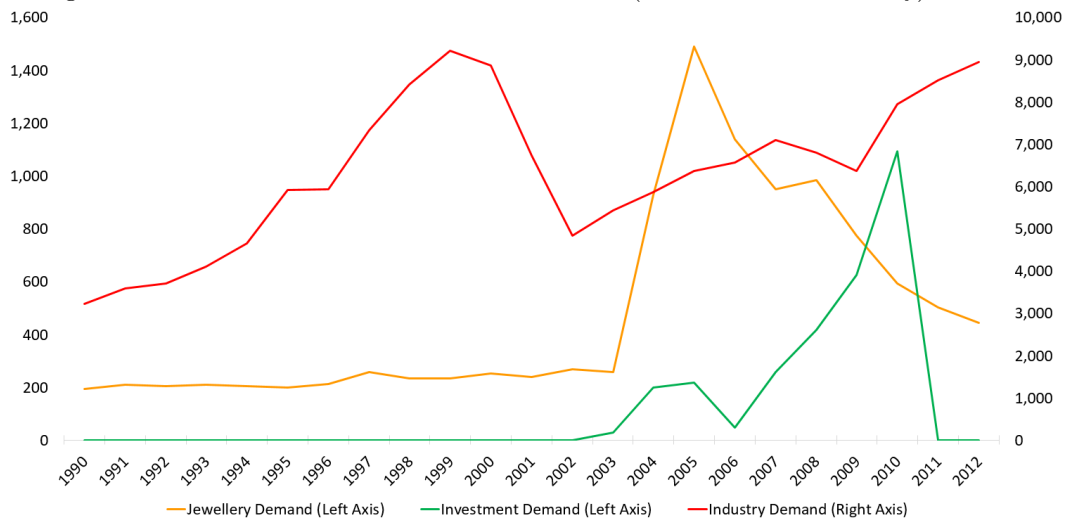


Figure 5: Directed Graph of HSMM

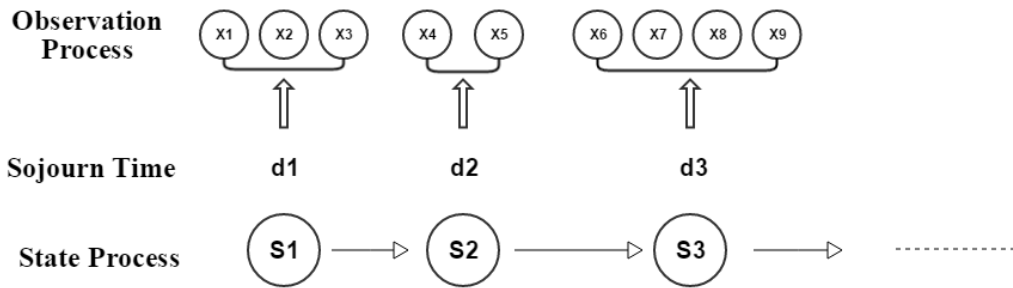


Figure 6: Dynamic Frequency Connectedness of Silver with Gold

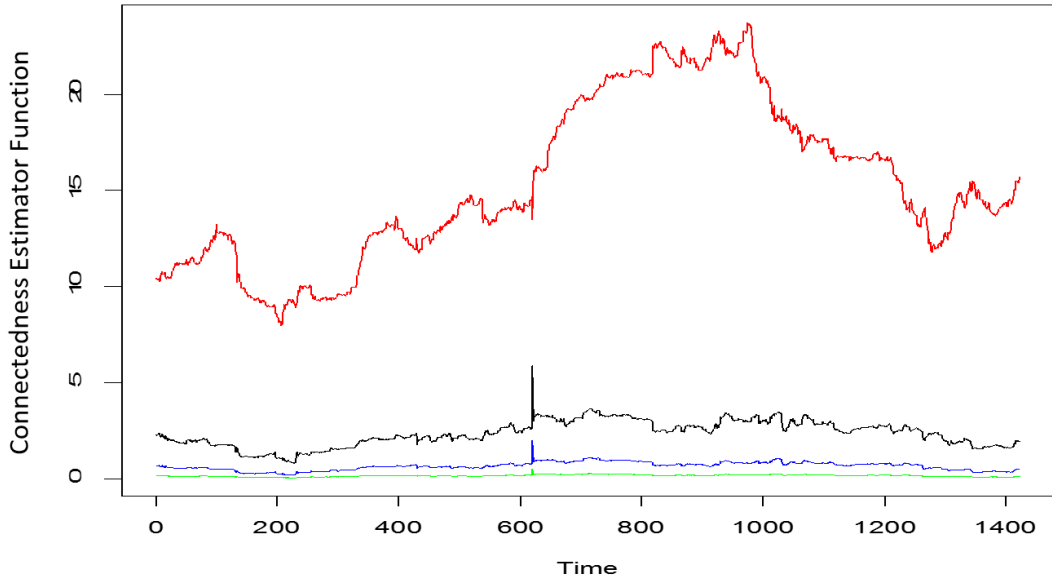


Figure 7: Dynamic Frequency Connectedness of Silver with Oil

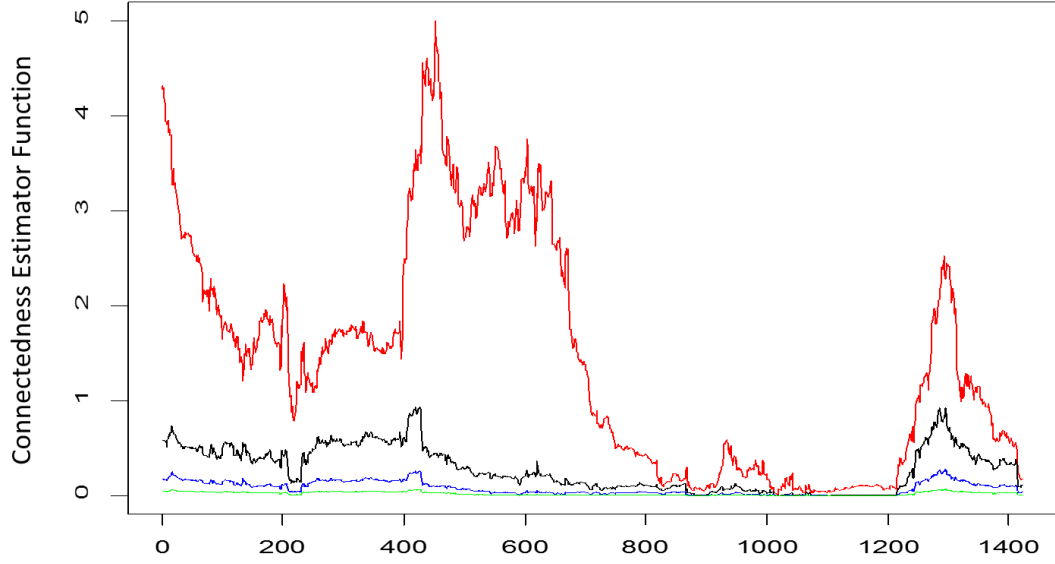


Figure 8: Dynamic Frequency Connectedness of Silver with Equity

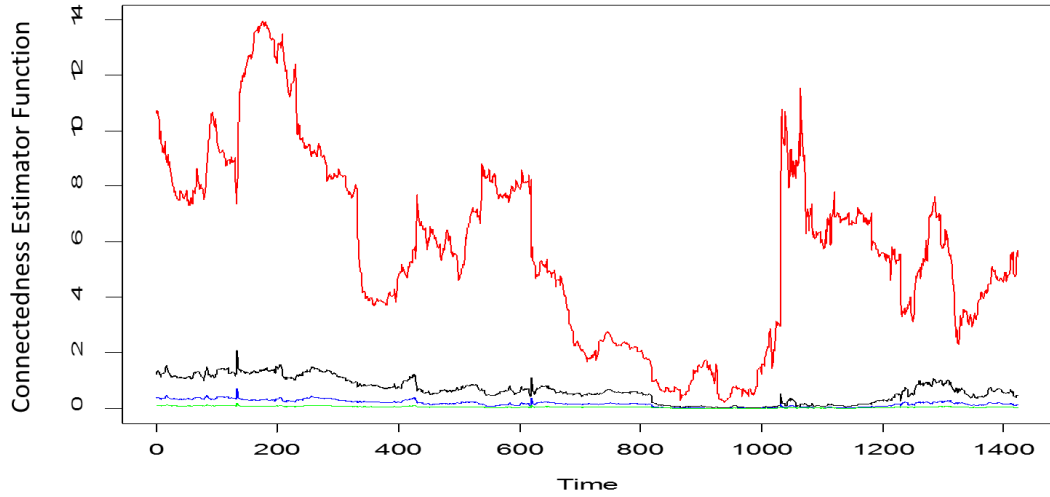


Figure 9: Dynamic Frequency Connectedness of Platinum with Gold

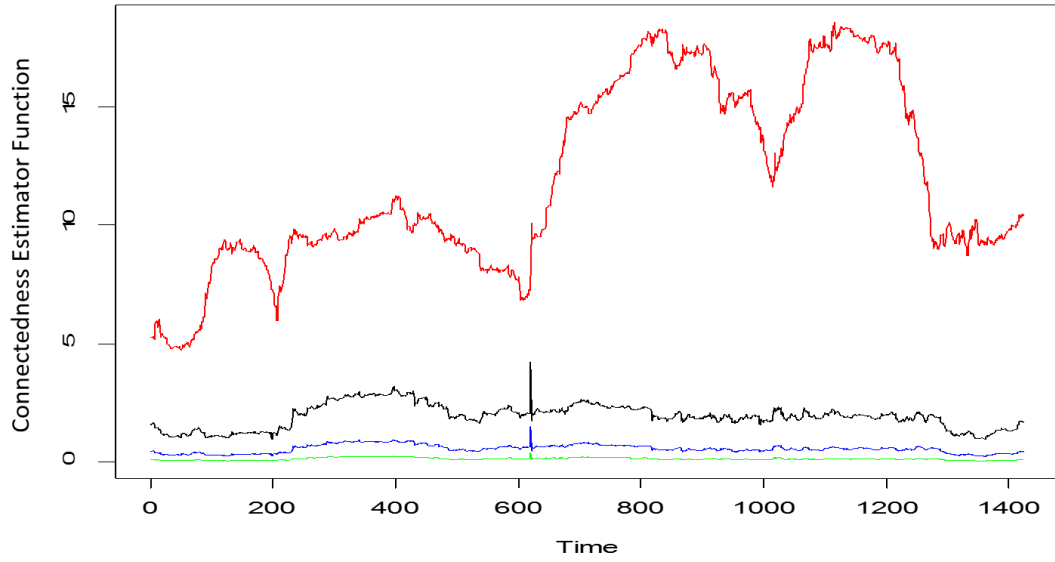


Figure 10: Dynamic Frequency Connectedness of Platinum with Oil

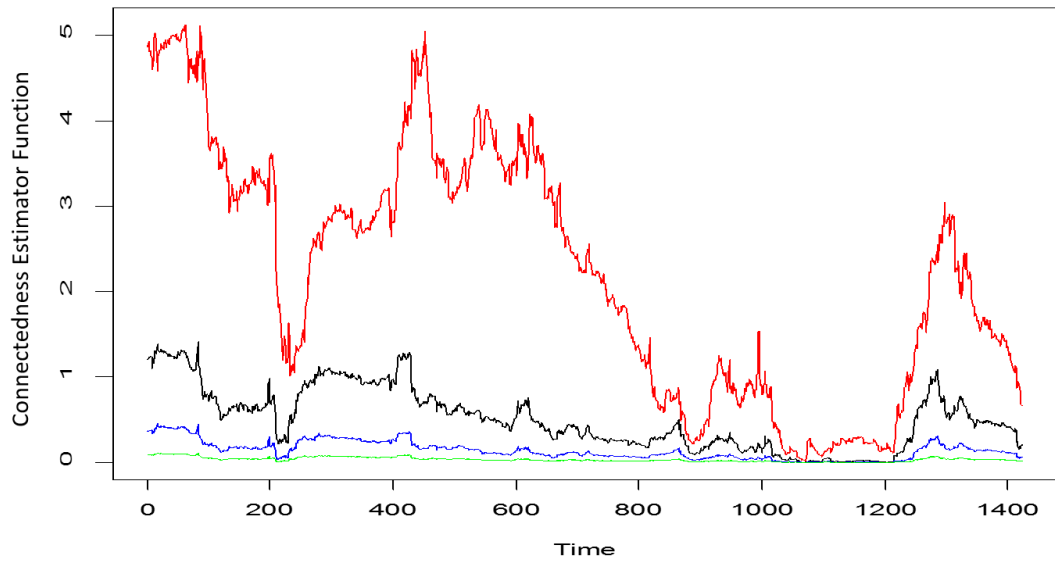


Figure 11: Dynamic Frequency Connectedness of Platinum with Equity

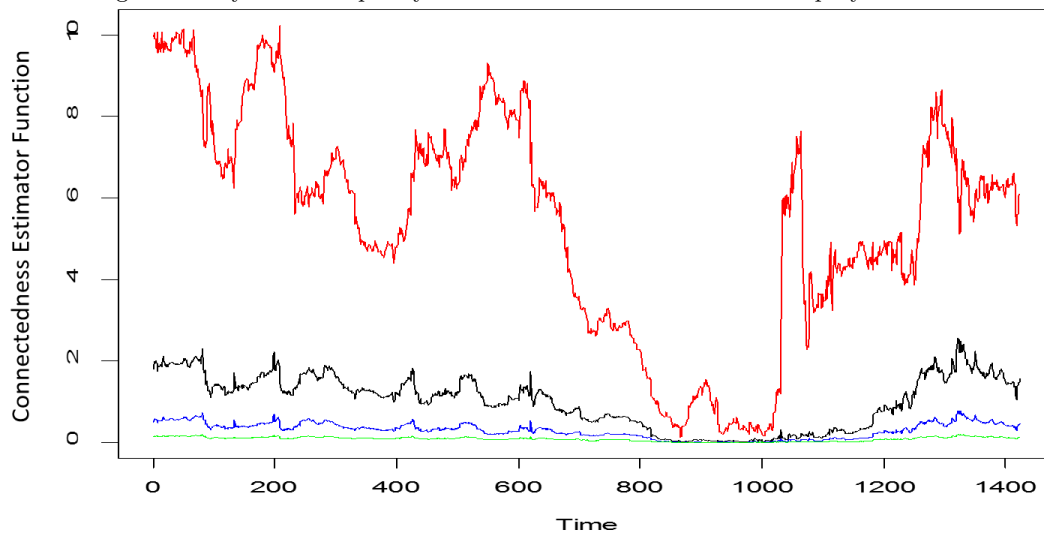


Figure 12: Dynamic Frequency Connectedness of Palladium with Gold

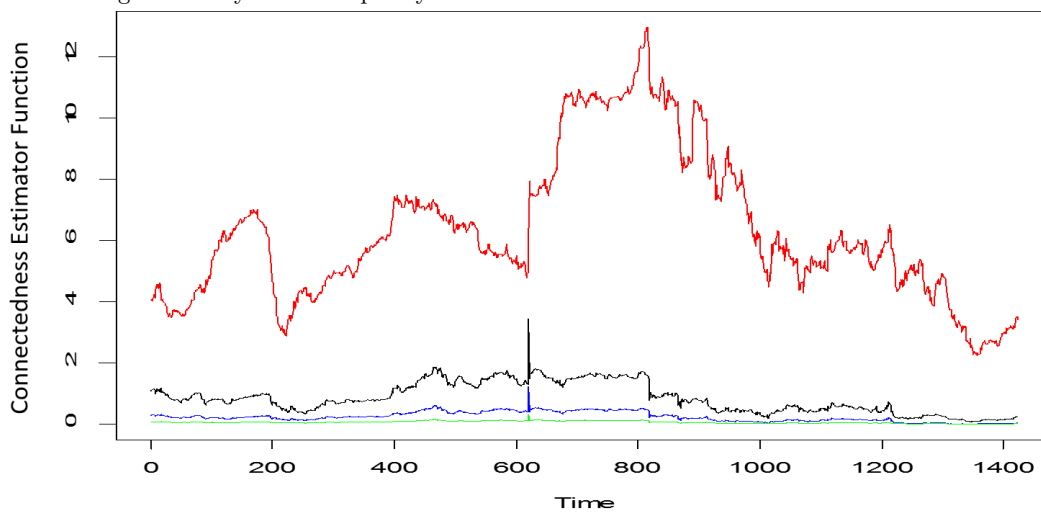


Figure 13: Dynamic Frequency Connectedness of Palladium with Oil

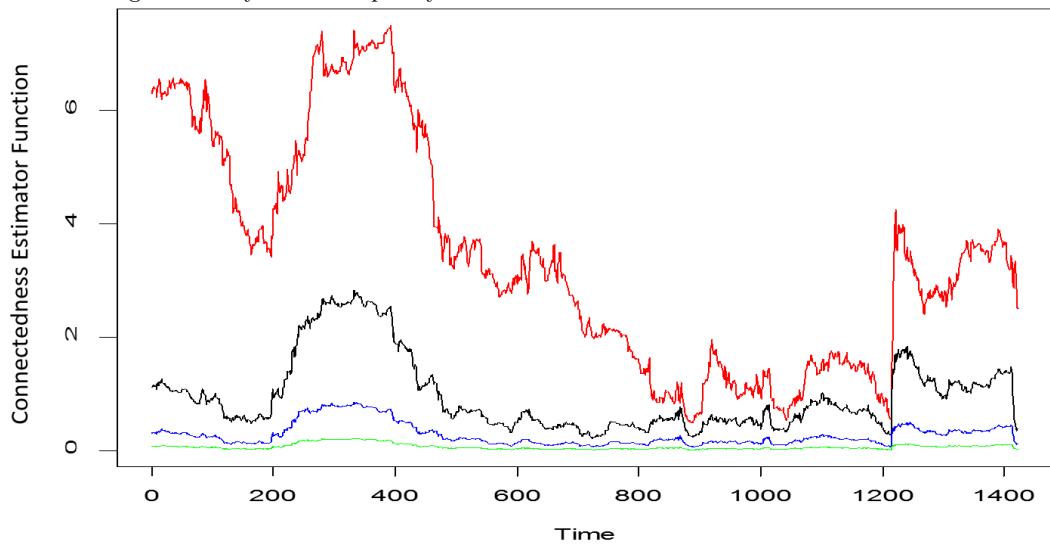


Figure 14: Dynamic Frequency Connectedness of Palladium with Equity

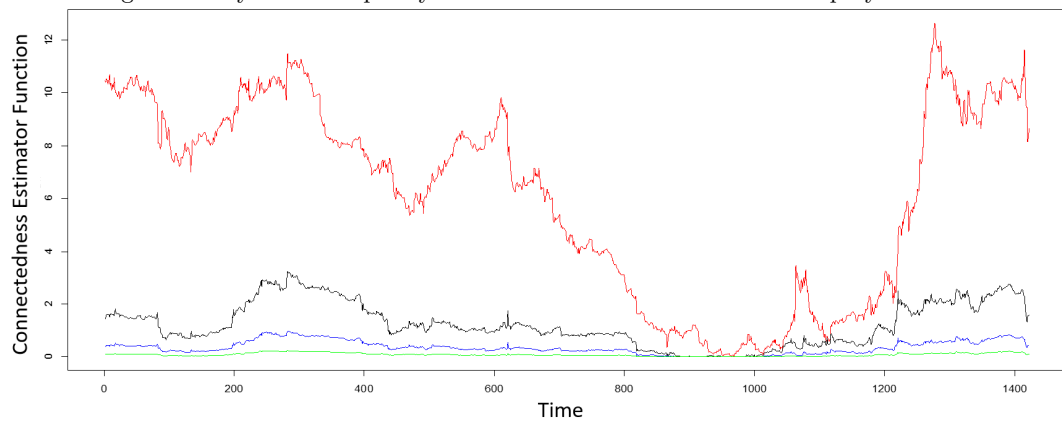


Figure 15: Global Decoding of Fitted two-state HSMM for Silver

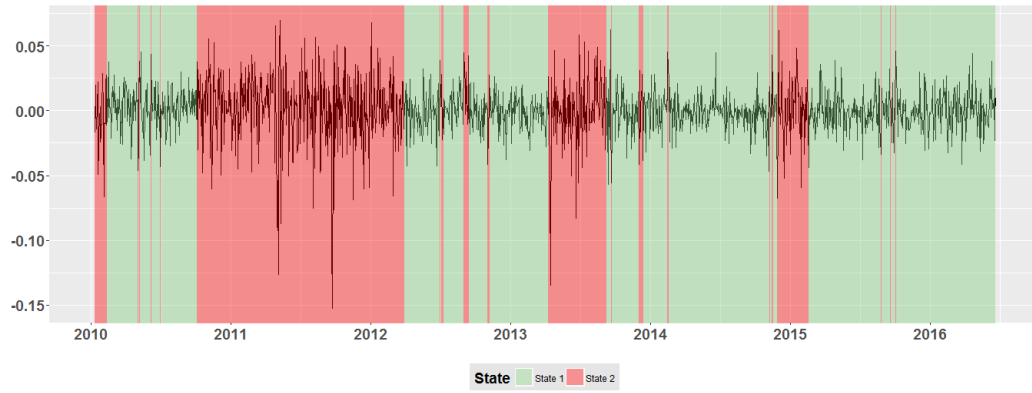


Figure 16: Global Decoding of Fitted two-state HSMM for Platinum

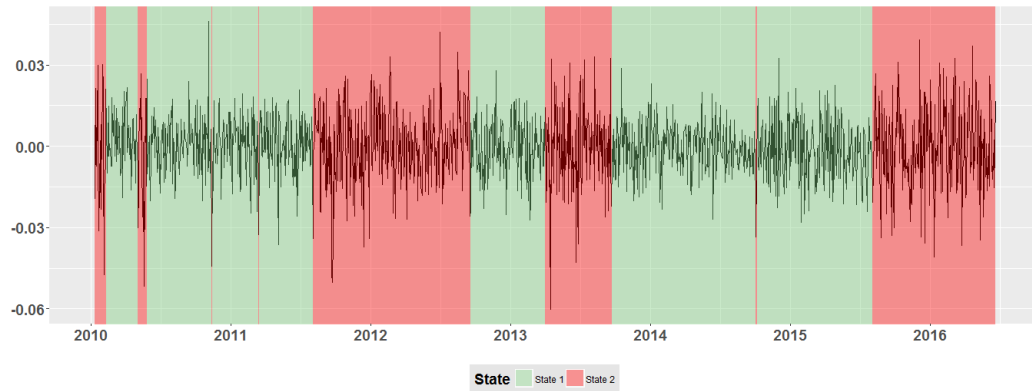


Figure 17: Global Decoding of Fitted two-state HSMM for Palladium

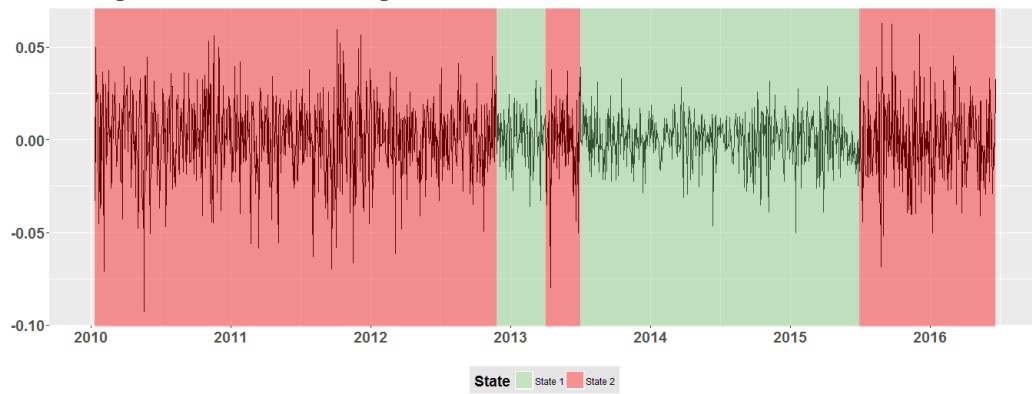


Figure 18: Global Decoding of Fitted three-state HSMM for Silver

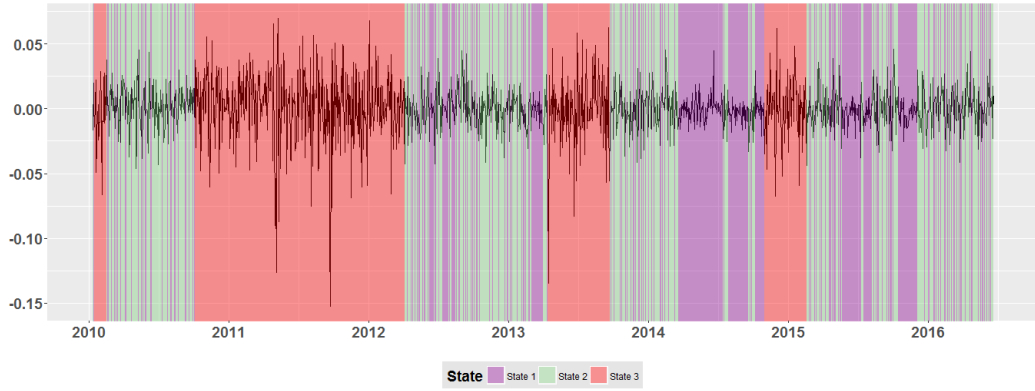


Figure 19: Global Decoding of Fitted three-state HSMM for Platinum

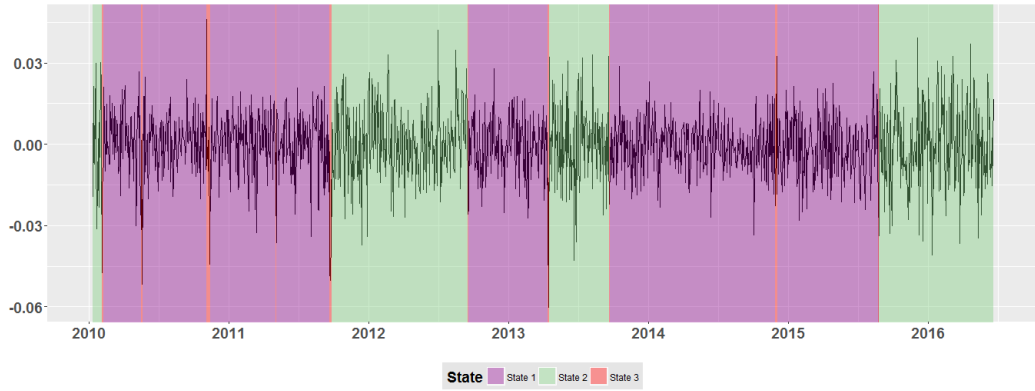


Figure 20: Global Decoding of Fitted three-state HSMM for Palladium

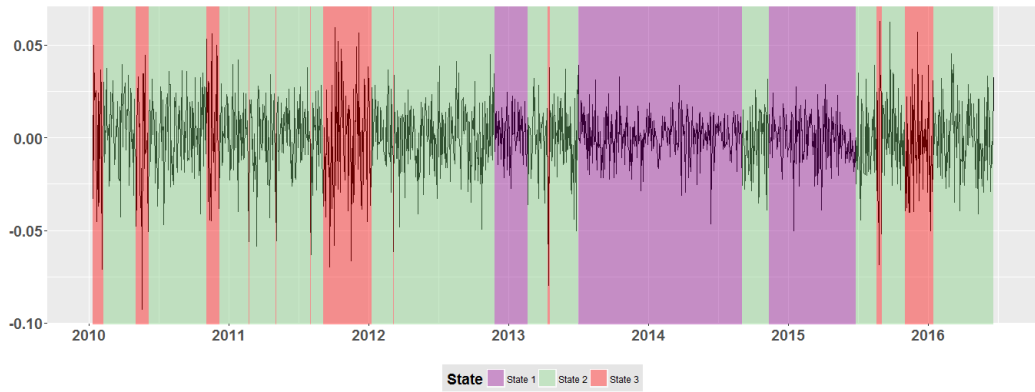


Table 1: Summary statistics of Silver, Platinum, Palladium, Gold, Oil and Equity ETF markets

	Silver	Platinum	Palladium	Gold	Oil	Equity
Mean	0.0002	-0.0003	0.0001	0.0003	0.0002	-0.0007
Median	0.0011	-0.0001	0.0008	0.0004	0.0008	-0.0003
Maximum	0.1347	0.0462	0.063	0.107	0.1207	0.0917
Minimum	-0.1983	-0.0602	-0.0926	-0.0919	-0.0982	-0.113
Std. Dev.	0.0216	0.0123	0.0185	0.0126	0.0131	0.0221
Skewness	-0.964	-0.2636	-0.3961	-0.2462	-0.2264	-0.148
Kurtosis	10.391	4.2321	4.4444	8.5961	12.634	5.3491

Jarque-Bera	6121.2	121.4	183.4	3311.1	9759.3	588.2
Probability	0.000	0.000	0.000	0.000	0.000	0.000

Table 2: Stationarity test with structural break

Panel A: Univariate unit root test/stationarity test		Innovation Outlier Test		
Variables	P-value (ADF)	P-value (PP)	P-value (Model A)	Break Date
Silver	0.000	0.000	0.000	20/07/2011
Platinum	0.000	0.000	0.000	15/01/2013
Palladium	0.000	0.000	0.000	11/03/2010
Gold	0.000	0.000	0.000	15/01/2013
Oil	0.000	0.000	0.000	10/01/2011
Equity	0.000	0.000	0.000	01/06/2011

Regarding the PP test, the selected truncation for the Bartlett Kernel are based on the suggestion by Newey and West (1994). The optimum lag order is selected based on the BIC criterion. The Innovation outlier test follows Perron (1989) assuming that the breaks occur gradually while following the same dynamic path as the innovations. Results for univariate unit root tests with structural breaks are based on the asymptotic one-sided p-values of Vogelsang (1993).

Table 3: Hatemi-J (2008) Cointegration Test Results

Marekts	Zt* test statistic	CV_1%	CV_5%	Break one	Break two	Conclusion
Palladium-Gold	-37.459***	-7.903	-8.353	19/01/2011	07/11/2011	Cointegrated
Palladium-Equity	-34.562***	-7.903	-8.353	21/01/2011	-	Cointegrated
Palladium-Oil	-38.002***	-7.903	-8.353	22/04/2011	-	Cointegrated
Platinum-Gold	-38.276***	-7.903	-8.353	20/02/2013	12/02/2014	Cointegrated
Platinum-Oil	-39.464***	-7.903	-8.353	27/03/2013	13/06/2014	Cointegrated
Platinum-Equity	-39.193***	-7.903	-8.353	15/04/2013	17/03/2014	Cointegrated
Silver-Gold	-41.551***	-7.903	-8.353	03/08/2011	20/04/2012	Cointegrated
Silver-Oil	-40.724***	-7.903	-8.353	27/04/2011	24/04/2012	Cointegrated
Silver-Equity	-41.041***	-7.903	-8.353	17/08/2011	12/04/2012	Cointegrated

The Critical values are obtained from Hatemi-J (2008). *** indicates rejection of the null hypothesis of no cointegration at the 1% levels.

Table 4: Influence on Silver ETF

	Coefficient	Std. Error	z-Statistic	Prob.
Panel A: Mean Equation				
δ_0	-0.0148	0.0002	-0.1123	0.9106
λ_1	0.0187	0.0116	1.6219	0.1048
δ_1 (GLD)	1.2813***	0.0178	72.0569	0.0000
δ_2 (USO)	0.2685***	0.0238	11.2723	0.0000
δ_3 (VTI)	0.0788***	0.0125	6.3000	0.0000
Panel B: Variance Equation				
ω	-0.3999	0.0932	-4.2896	0.0000
α_1	0.2109	0.0287	7.3394	0.0000
γ_1	0.0053	0.0185	0.2879	0.7734
β_1	0.9741	0.0090	107.8562	0.0000
GED Parameter	1.317	0.0660	19.9617	0.0000
Adjusted R^2	0.6854			

***, ** and * indicate the 1%, 5%, and 10% significance levels, respectively.

Table 5: Influence on Platinum ETF

	Coefficient	Std. Error	z-Statistic	Prob.
Panel A: Mean Equation				
δ_0	-0.0004	0.0002	-2.2800	0.0226
λ_1	0.0529	0.0152	3.4694	0.0005
δ_1 (GLD)	0.7300***	0.0162	45.1628	0.0000
δ_2 (USO)	0.2538***	0.0205	12.3880	0.0000
δ_3 (VTI)	0.0723***	0.0104	6.9353	0.0000
Panel B: Variance Equation				
ω	-0.4396	0.1365	-3.2192	0.0013
α_1	0.1232	0.0295	4.1734	0.0000
γ_1	<u>0.0126</u>	0.0156	0.8062	0.4201
β_1	0.9646	0.0127	75.7151	0.0000
GED Parameter	1.6885	0.0790	21.3685	0.0000
Adjusted R^2	0.5713			

***, ** and * indicate the 1%, 5%, and 10% significance levels, respectively.

Table 6: Influence on Palladium ETF

	Coefficient	Std. Error	z-Statistic	Prob.
Panel A: Mean Equation				
δ_0	-0.0001	0.0003	-0.2319	0.8166
λ_1	0.0705	0.0185	3.8083	0.0001
δ_1 (GLD)	0.6525***	0.0306	21.3042	0.0000
δ_2 (USO)	0.5500***	0.0361	15.2387	0.0000
δ_3 (VTI)	0.1608***	0.0197	8.1770	0.0000
Panel B: Variance Equation				
ω	-0.2621	0.0946	-2.7719	0.0056
α_1	0.0818	0.0248	3.3039	0.0010
γ_1	<u>-0.0301</u>	0.0149	-2.0143	0.0440
β_1	0.9768	0.0099	98.5405	0.0000
GED Parameter	1.4925	0.0681	21.9129	0.0000
Adjusted R^2	0.4052			

***, ** and * indicate the 1%, 5%, and 10% significance levels, respectively.

Table 7: Total Connectedness of White Precious Metal Markets over Different Time Intervals

Weekly Cycle	Palladium	Platinum	Silver	Gold	Equity	Oil	From Others*	Net	Conclusion
Palladium	38.413	12.738	12.356	5.071	6.74	3.72	40.625	19.817	net-contributor
Platinum	18.131	24.388	18.234	10.565	5.261	1.803	53.995	-6.712	net-recipient
Silver	10.787	11.424	39.318	14.085	5.108	0.944	42.348	29.287	net-contributor
Gold	9.331	14.09	30.559	26.462	2.283	0.031	56.294	-25.192	net-recipient
Equity	8.517	4.54	6.759	1.313	53.983	6.228	27.357	8.541	net-contributor
Oil	13.675	4.492	3.726	0.068	16.506	41.276	38.466	-25.741	net-recipient
Contribution to others**	60.441	47.284	71.634	31.102	35.898	12.725	259.085		
Contribution including own***	98.854	71.672	110.952	57.564	89.881	54.001	43.18%		
Monthly cycle									
Palladium	7.4544	2.342	2.2503	0.7858	1.4282	1.1569	7.9633	3.051	net-contributor
Platinum	3.6284	4.8123	3.7193	2.0102	1.1417	0.561	11.0606	-2.7109	net-recipient
Silver	1.9861	1.9665	6.3555	2.2873	0.7004	0.2825	7.2228	5.4673	net-contributor
Gold	1.5114	2.2946	4.612	4.1082	0.2216	0.0151	8.6546	-3.2294	net-recipient
Equity	1.4325	0.8375	1.2628	0.2974	8.7946	1.0798	4.9101	2.2957	net-contributor
Oil	2.4558	0.9092	0.8456	0.0444	3.714	6.8862	7.969	-4.8737	net-recipient
Contribution to others**	11.0143	8.3498	12.6901	5.4252	7.2058	3.0953	47.7804		
Contribution including own***	18.4687	13.1621	19.0456	9.5334	16.0004	9.9815	7.96%		
Quarterly cycle									
Palladium	2.129	0.668	0.643	0.223	0.423	0.349	2.306	0.809	net-contributor
Platinum	1.027	1.395	1.085	0.59	0.332	0.166	3.199	-0.823	net-recipient
Silver	0.555	0.551	1.783	0.646	0.191	0.082	2.024	1.624	net-contributor
Gold	0.423	0.646	1.292	1.163	0.058	0.004	2.423	-0.857	net-recipient
Equity	0.412	0.244	0.375	0.092	2.521	0.318	1.443	0.672	net-contributor
Oil	0.699	0.266	0.252	0.015	1.113	1.976	2.345	-1.425	net-recipient
Contribution to others**	3.116	2.376	3.647	1.566	2.115	0.92	13.74		
Contribution including own***	5.245	3.771	5.43	2.729	4.636	2.896	2.29%		
Yearly cycle									
Palladium	0.532	0.167	0.161	0.056	0.106	0.088	0.577	0.201	net-contributor
Platinum	0.256	0.349	0.272	0.148	0.083	0.042	0.8	-0.207	net-recipient
Silver	0.138	0.137	0.445	0.161	0.047	0.021	0.505	0.407	net-contributor
Gold	0.106	0.161	0.322	0.291	0.014	0.001	0.605	-0.213	net-recipient
Equity	0.103	0.061	0.094	0.023	0.63	0.08	0.361	0.168	net-contributor
Oil	0.175	0.067	0.063	0.004	0.279	0.494	0.587	-0.357	net-recipient
Contribution to others**	0.778	0.594	0.912	0.392	0.53	0.231	3.437		
Contribution including own***	1.311	0.943	1.357	0.682	1.16	0.725	0.57%		

* From others: Measures spillovers from all markets j to market i ; ** Contribution to others: Measures spillovers from market i to all markets j ; *** Contribution including own: Measures spillovers from market i to all markets j , including contribution from own innovations to market i . The other columns contain net pairwise (i,j) -th spillovers indices.

Table 8: Estimation Results of Two-state HSMM

		Palladium		Platinum		Silver	
		State 1	State 2	State 1	State 2	State 1	State 2
Conditional Distribution	Mean*10000	11.406	-8.48	-0.931	-6.714	1.217	-3.947
	Variance*10000	1.356	5.364	0.845	2.562	1.329	8.839
	z-statistic	2.375	-1.177	-0.312	-1.089	0.336	-0.327
Sojourn Time	r	0.051	0.098	0.686	0.058	0.146	0.019
	p	0.013	0.023	0.061	0.008	0.04	0.014
	No. of Days	588	1034	948	674	1015	607
	Average Sojourn Time	117.6	206.8	94.8	61.263	17.203	10.466

Table 9: Estimation Results of Three-state HSMM

		Palladium			Platinum			Silver		
		State 1	State 2	State 3	State 1	State 2	State 3	State 1	State 2	State 3
Conditional Distribution	Mean*10000	6.224	12.142	-39.573	-0.844	5.546	-69.091	-6.255	12.298	-24.461
	Variance*10000	1.165	2.832	8.301	0.939	2.096	4.593	0.397	3.31	10.87
	z-statistic	1.298	2.155	-2.051	-0.278	0.923	-1.644	-2.193	1.581	-1.798
TPM	State 1	0.00%	99.96%	0.04%	0.00%	0.09%	99.91%	0.00%	93.86%	6.14%
	State 2	23.25%	0.00%	76.75%	0.42%	0.00%	99.58%	93.07%	0.00%	6.93%
	State 3	0.04%	99.96%	0.00%	36.76%	63.24%	0.00%	0.00%	100.00%	0.00%
Sojourn Time	r	0.375	2.148	0.428	2.874	0.12	6.741	0.044	9.524	0.072
	p	0.008	0.091	0.049	0.043	0.007	0.848	0.072	0.878	0.012
	No. of Days	507	892	223	1016	580	26	488	547	587
	Average Sojourn Time	169	63.714	20.273	145.143	116	2.364	2.085	2.348	146.75