

**\Information Transmission, Nonlinearity and
Volatility Behavior of Precious Metals in the
Presence of Oil and Exchange Rate Shocks**

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ABSTRACT

The recent shock waves due by devastating and contagious crises in both the stock and commodity markets over the last few decades have driven individual investors, institutions, as well as entire countries to bankruptcy. Smart investors have realized and therefore seized the potential advantages inherent in alternative investments particularly in precious metals. In this study, we investigate information diffusion, nonlinearity and chaotic structure in a regime changing environment, volatility convergence and persistence, and information asymmetry in these precious metal prices in the presence of oil and exchange rate shocks. Under the prefix that our selected precious metals (gold, silver, platinum and palladium) move in tandem when exposed to similar macroeconomic fundamentals, we use the Vector Error Correction Model (VECM) to analyze the long run relationship amongst these precious metal prices.

On nonlinearity and chaotic structure in a regime-switching environment, we use the Bayesian Markov-Switching vector error correction (MS-VEC) model and the regime-dependent impulse response functions (RDIRF) to examine the transmission dynamics between these commodities. Finally, we use the GARCH (2, 2) and the Threshold-GARCH (2, 2) models to investigate volatility persistence and convergence, as well as the impact of asymmetric (positive and negative) shocks on the precious metal prices. We maintain consistency by using the same long range high frequency data from 1987 to 2012 for the entire study. Moreover, we use

compelling time series techniques for the analysis as well as consider the structural breaks and shocks inherent over the span of our sample.

We find a co-integration relationship between these variables as well as significant short term interactions both pre and post 2007/2008 financial crisis. We find compelling evidence that gold is most informative in the group over the entire sample period. Rising oil prices is seen to be pro-cyclical with precious metal prices mainly post crisis since it is a complement in precious metal production. Platinum price changes explain changes in palladium price returns but the reverse is not true.

Furthermore, two regimes (low and high volatility regimes) appear prevalent for this study. Gold prices are clearly the most informative in the group in the high volatility regime, while gold, palladium, and platinum are the most informative in the low volatility regime. Moreover, although the platinum and palladium prices impact each other, the impacts in the high volatility regime are asymmetric. In addition to its low correlation in the group, palladium's negative impact on the exchange rate and gold makes it a reliable hedge asset for investors. Gold is the least volatile variable, thus affirming its use as a "*safe haven*" asset, while silver and oil are the most volatile in the group.

Regarding volatility behavior of precious metals, there is slow convergence or high persistence for the investment and monetary assets (gold and silver) than the more industrial commodities (platinum and palladium). Gold and silver are seen to adjust more quickly to shock than their industrial counterparts. In addition, gold and silver portray asymmetry regarding good and bad news on the conditional variance. Although both gold and silver exhibit resistant to the AFC, silver is a lot more

vulnerable than gold as seen by the news impact curves. This may be a result of the lost monetary element of silver which has become more of an industrial than a monetary unit over the past decades. Gold and silver show some leverage effect while platinum and palladium show insignificant leverage effect.

Although there are possible extensions to this study, many stakeholders will benefit significantly from the results of this study. International investors may consider including palladium in their precious metal portfolios since its low correlation makes it a good hedge asset. Particularly during high volatility regimes, investors of precious metal, central banks and other stakeholders should watch gold and oil prices carefully especially due to their high information content in determining the direction of change in the other commodity prices and exchange rate, and its ability to act as a cushion during inflationary periods. Moreover, investors can make reliable forecasts in different regimes, while hedgers will turn to gold and maybe silver particularly during crisis, while using palladium as a portfolio diversifier regarding investing in precious metals. Consumers' purchase decisions for durable goods would be more accurate if they understand the relationship between the commodities since these durables are made from some of these metals. Moreover, major oil importers/exporters as well as oil traders may benefit from these findings by monitor oil price changes especially post crisis.

Keywords: GARCH, generalized forecast error variance decomposition, generalized impulse response, information transmission, Markov-Switching VEC model, oil prices, precious metal prices, regime-switching, TGARCH volatility.

ÖZ

Son zamanlarda ekonomilerde gözlemlenen şok dalgaları hem hisse senedi piyasalarında hem de emtia piyasalarında zararlı etkisini göstermiş bireysel yatırımcıları, kurumları ve hatta ülkelerin tamamını iflasın eşiğine getirmiştir. Krizin farkına varan akıllı yatırımcılar doğal olarak alternatif yatırımlara özellikle de değerli metallara yönelmişlerdir. Bu tezde amaçlanan petrol ve döviz kuru şoklarının değerli metaller üzerindeki bilgi yayılımı, doğrusalsızlık, volatilité yakınsaması ve direnci, rejimi değişen çevredeki kaotik durum ve asimetrik bilgi gibi konseptlerle alakalı durumunu incelemektir.

Çalışmada seçilen değerli metaller (altın, gümüş, platinyum ve palladyum olarak sıralanmakta) ve bu metallerde benzer temel makroekonomik gösterge değişiklikleri gözlemlenmektedir. 2007/2008 finansal krizin öncesi ve sonrasında bu değerli metallerin fiyatlarının nasıl değiştiğini analiz edebilmek için genelleştirilmiş tahmini hata varyas ayrıştırma ve genelleştirilmiş etki tepki fonksiyonları kullanılmıştır.

Rejimi değişen çevrenin doğrusalsızlık ve kaotik durum analizi için de Markov Switching vektör hata düzeltme methodu ve rejime bağlı etki tepki fonksiyonu aktarım dinamiklerini ölçmek için kullanılmıştır. Son olarak, GARCH (2, 2) ve eşik GARCH (2, 2) modelleri kullanılarak değerli metal fiyatları üzerindeki direnç ve yakınsama etkileri ve asimetrik (pozitif ya da negatif) şokların etkileri ölçülmüştür. Çalışmanın tamamında aynı uzunlukta tutarlı bir veri seti (1987den 2012ye kadar) kullanılmıştır. İlâveten analiz boyunca zorlayıcı zaman serisi teknikleri kullanılmış, yapısal kırılmalar ve doğal şoklar da örneklem için dikkate alınmıştır.

Çalışmanın sonucunda bu değişkenler arasında hem 2007/2008 finansal krizi öncesinde hem de sonrasında eş bütünleşme ve kısa dönem etkileşimler tespit edilmiştir. Çalışmamızın bulguları altının grup içerisinde en belirleyici metal olduğuna işaret etmektedir. Gümüş üzerinde kriz öncesinde ve sonrasında %34 ve %36 düzeyinde etkin olmuştur. Yükselen petrol fiyatları pro konjonktürel olarak

özellikle kriz döneminden sonra karşımıza çıkmaktadır. Değerli metallerin hammadesi olması da bunda önemli bir etkidir. Platinyum fiyat değişimleri palladyum fiyat değişimlerini açıklar niteliktedir. Ancak bu sonucun tersini söylemek mümkün değildir. IRF 2 günlük spekülatif pencerede asimetric bilgiye ve bir sonraki gün için de aşırı reaksiyonlara işaret etmektedir.

Ilaveten bu çalışmada iki rejim (düşük ve yüksek volatilitate rejimleri) yaygın olarak karşımıza çıkmaktadır. Yüksek volatilitate rejiminde altın fiyatları karşımıza en belirleyici olarak çıkarken düşük volatilitate rejiminde gümüş platinyum ve palladyum karşımıza en belirleyici olarak çıkmaktadır. Dahası platinyum ve palladyum fiyatları birbirlerini etkilerken yüksek volatilitede bu etkiler karşımıza asimetric olarak çıkmıştır. Gruptaki düşük korelasyona ek olarak, palladyumun döviz kuru üzerindeki negatif etkisi ve altın durumu yatırımcılar için güvenli bir çit haline getirmektedir. Grup içerisinde en düşük volatilitate altında gözlemlenmiştir. Bu da altını en güvenli yatırım aracı haline getirmektedir. Bununla beraber gümüş ve petrol bu gruptaki en volatilitesi yüksek olan metaller olarak karşımıza çıkmıştır.

Volatilitate davranışı bakımından değerli metallerden yatırım ve parasal varlıklar olarak karşımıza çıkan altın ve gümüşte düşük yakınsama ve yüksek direnç karşımıza çıkarken endüstriyel varlıklarda (platinyum ve palladyum) bu daha düşük olarak gözlemlenmektedir. Altın ve gümüşün endüstriyel olarak kullanılan diğer iki değerli metalden daha çabuk şoktan kurtulduğunu söylemek mümkündür. Ek olarak altın ve gümüş koşullu varyansı incelediğimizde asimetric bakımından hem iyi hem de kötü olarak karşımıza çıkmıştır. AFC karşısında altın ve gümüşün dirençli oldukları dikkate alınmakla beraber faktör eğrilerine karşı gümüşün çok daha kırılğan olduğu gözlemlenmiştir. Bu durum gümüşün yatırım değerinden uzaklaşarak son yıllarda endüstriyel alanda kullanımının artış göstermesiyle açıklanabilir. Altın ve gümüş belirli miktarda baskı etkisi gösterirlerken platinyum ve palladyum önemsiz baskı etkileri göstermişlerdir.

Bu çalışmanın çeşitli açılardan genişletilmesi mümkündür. Hali hazırda ise paydaşlar önemli ölçüde bu çalışmadan faydalanabilirler. Uluslararası yatırımcılar palladyumu değerli metal portfolyosunda kullanmaya devam edebilirler. Çünkü düşük

korelasyon bu metali güvenli bir çit haline dönüştürmektedir. Yüksek volatiliteli rejim döneminde değerli metal yatırımcıları, merkez bankaları ve diğer pay sahipleri altın ve petrol fiyatlarını dikkatlice takip etmelidirler. Bunun sebebi altın ve petrolün yüksek bilgi içerikleri sayesinde diğer varlıkların fiyat değişiminde ve döviz kurundaki değişmelerde önemli rol oynayabilmeleri ve yüksek enflasyon döneminde minder etkisi gösterebilmeleridir. İlâveten yatırımcılar farklı rejimlerde güvenilir tahminler yapabilirler. Çünkü kriz döneminde altın ve gümüşe yönelim artarken palladyum portfolyoda bir çeşitlendirici görevi görmektedir. Tüketicilerin dayanıklı tüketim mallarını satın almasındaki kararlılıkları bu tüketim mallarının değerli metallerin bir kısmından üretildiğini anlamaları halinde olumlu yönde değişim gösterecektir. İlâveten majör petrol ihracatı ve ithalatı yapan ülkelerin fiyatlardaki dalgalanmaları dikkatlice takip etmesi özellikle krizler sonrasında önemli bir adım olacaktır.

Anahtar Kelimeler: GARCH, genelleştirilmiş hata payı varyans ayrıştırması, genelleştirilmiş etki tepki, bilgi aktarımı, Markov-Switching VEC modeli, petrol fiyatları, değerli metal fiyatları, rejim değişimi, TGARCH volatilitesi.

DEDICATION

To My Family

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criterion
AFC	Asian Financial Crises
BIC	Bayesian Information Criterion
COMEX	Commodity Exchange Incorporation
CRB	Commodity Research Board
D or Δ	Difference Operator
FFBS	Forward Filter-Backwards Sampling
GFC	Global Financial Crises
L or Log	Natural Logarithm
MCMC	Markov-Chain Monte Carlo
ML	Maximum Likelihood
MS-VEC	Markov-Switching Vector Error Correction
RDIRF	Generalized Impulse Response Function
SIC	Schwarz Bayesian Information Criterion
VAR	Vector Auto Regressive
VEC	Vector Error Correction

Chapter 1

INTRODUCTION

1.1 Introduction

Over the last half century, international trade has expanded dramatically beyond borders, investment in shares, bonds and in commodities, as well as the derivatives markets have also expanded unprecedentedly. Markets have become highly integrated both in the developed and developing countries. In fact, the speedy growth and high profit potential of some emerging economies like China, India, and Turkey etc. have cause investors and traders to rethink their investment strategies in emerging markets over the last few decades. However, while the benefits of globalization, trade diversity and reduced transaction time and costs have sprung from rapid technological growth, it has also encouraged financial unrestrained behavior by several market participants. This persistent financial indiscipline has led to contagious market failures and economic crises in the last few decades.

The Asian Financial Crisis (1997-1998) which stemmed from short-term capital movements in South Asia was highly contagious to other financial markets. The new millennium was accompanied by 2001 U.S recession due to failure of the internet technology burst which propelled excess liquidity. Furthermore, the 2007/2008 mortgage crisis led to the collapse of the real estate market in the U.S, and a subsequent spillover to other financial markets worldwide. These crises increased volatility in the stock and commodity prices, and their contagious effects spread

throughout different financial markets. (Forbes and Rigobon, 2002; Lee et al., 2007; Markwat et al., 2009). The contagion that was thrust by failing financial markets led investors to question the core reliability of traditional investments in stocks and bonds. Some investors came to recognize that diversified through alternative investments such as precious metals could be very lucrative particularly during crisis.

The substantial demand for oil coupled with the more diversified uses of precious metals in industries such jewelry, photography, medical and automobile have ignited the interest of investors to trade these commodities on international financial markets. Historically, these precious metals tend to move in synch¹ particularly when exposed to akin macroeconomic variables like interest rates, inflation and industrial productivity. Their synchronized movements over the years have facilitated analyzing their boom-burst patterns and propelled them to become reliable investment assets (Hammoudeh et al., 2008). These selected precious metals occur naturally and exhibit peculiar properties. Their uses are broad and their prices have been known to move in unison over the last few decades. Zhang et al. (2010) find unidirectional causality between oil and gold prices, as well as a 92.95% correlation between them. A plausible reason for the movement of these commodities in tandem² is because they are inputs in similar processes (e.g. oil is a major input in metals productions) and can be used in place of others in some production processes (e.g. platinum and palladium substitute one another for making catalytic converters). Moreover, these commodity prices behave similarly macroeconomic shocks. In fact,

¹Pindyck and Rotemberg (1990) amongst others suggest that unconnected commodities show strong correlation in their price movements. Cashin et al., (1999) disagree to this assertion. Travedi (1995) amongst others, find no “excess” co-movement.

² Beahm (2008) state that there is a procyclical movement between gold and oil prices and also posit that this relationship is one of the five major explanations for the instability in precious metal prices especially gold in the United States.

some researchers posit that the co-movements of commodity prices convey more reliable information to market participants than consumer prices (Mahdavi and Zhou, 1997). The information contained in commodity futures prices, risk sharing and information discovery provides a channel for speculative trading in futures markets. All these account for a rich understanding of the financialization of commodity prices which is reflected in their spot and their increasing popularity amongst investors prices (Hu and Xiong, 2013)

The comprehensive objective of this study is to examine the information transmission dynamics of selected precious metals (gold, silver, platinum and palladium), while accounting for shocks in oil prices and exchange rates. To attain this objective, this thesis will be separated into three major sections namely: information diffusion, nonlinearity and chaotic behavior, and volatility transmission, in an attempt to answer several pertinent questions. Pindyck and Rotemberg (1990) were the pioneers who studied a group of related and unrelated commodity prices and concluded that they move together when exposed to similar economic variables. While there are many proponents to this conception, other researchers like Cashin et al., (1991) amongst others do not agree that unrelated commodities move together. The key questions that this thesis will attempt to unravel are as follows:

First; if the prices of these designated precious metal prices move in tandem when exposed to akin macroeconomic variables, how do we know ones whose prices trigger the others, and to what extent is this significant? Which of them transmits the highest information? Are these price co-movement evident or differ before and after crises? Notably, there has been some research on this area such as those of Claire Schaffnit-Chatterjee (2012), Abidi et al., (2013), Wiggins & Keats (2009), etc.

Unlike former studies, this study differs in that we focus on selected and related precious metals and not agricultural commodities. On the other hand, many earlier works have concentrated a mixture of unrelated commodities (agricultural and industrial) rather than related commodities prices (see Palaskas and Varangis (1991), Palaskas (1993)) amongst others. However, we place our focus on related commodity prices particularly the four most prominent precious metals which have diversified industrial and investment potentials. The first part of this thesis contributes to fill this gap in the literature on commodity price transmission in the presence of economic fundamentals by addressing these concerns that arise amongst the different precious metal stakeholders.

Secondly, it would be interesting to unravel whether the co-movements in these selected precious metal prices differ or convey information given which state of the economy is dominant at the time. Given our data set, we will delve into the contention underscoring that these commodity prices move in a non-linear fashion and are dependent upon the latent state of the market. Adriangi and Chatrath (2002), Yang and Brorsen (1993), Goetz et al., (2010) etc. are a few of those that have research on non-linearity and chaotic structure in commodity prices. This section will seek to unravel whether the information transmission dynamics of these selected commodity prices depends on multiple latent regimes. We also seek answers to the inquiry as to: which of the commodities under consideration can be used as an effective hedge asset if their prices move in unison during normal and volatile states of the economy; and which commodities can be used as a “*safe haven*” during crises? We discriminate between the short-run and long-run subtleties, allow for nonlinearity and adequately specify the nonlinear dynamics between the variables of interest by identifying the potential latent regimes in the data. It is also important to consider

non-linearity and structural changes in light of the 2007/2008 credit crunch and the 2010-2012 European debt crisis. This section will add value to the research on non-linearity in commodity prices and chaotic structure.

Finally, the last part of this thesis aims at investigating volatility behavior of these selected precious metals while taking cognizance of oil and exchange rate shocks. Hereafter, using two GARCH family models, we investigate which amongst the precious metals is the most volatile. We seek to know whether positive and negative shock impact divergently, and also if any leverage effect is present in lieu of crisis amongst our selected precious metals. Volatility forecasting is very popular in the literature as supported by the works of Hammoudeh et al., (2004), (Reignier, 2007), Adriangi and Chatrath (2003), Morales, L., (2008) etc. This area is relevant in risk management, asset valuation and hedging strategies thus adding value to both the literature and aiding investors to make more informed decisions.

The three sections mentioned above will help to better comprehend the dynamics of our selected precious metal prices given oil and exchange rate shocks. We use broad daily time series data for a 25 year period spanning 01/05/1987 to 24/02/2012. This thesis will be structured as follows: Chapter 1 will introduce the study and state its motivation. Chapter 2 will review some literature given three major sections in the literature on commodity prices. Chapter 3 will examine the price dynamics in the presence of economic fundamentals. Chapter 4 will investigate nonlinearity and how the prices behave in different latent regimes. Chapter 5 will evaluate volatility persistence and convergence of these commodity prices while Chapter 6 will conclude and make some policy recommendations.

Chapter 2

LITERATURE REVIEW

There is much empirical literature on the behavior of commodity prices. Three major subdivisions stand out upon scrutiny of the literature on commodity prices that relate to the current research namely; co-movement of commodity prices, substantial diffusion while considering fundamental macroeconomic variables, and volatility behavior (Bhar and Hammoudeh, 2011). In the literature, research on commodities like copper, oil and agricultural commodities are broader in identifying major links and inter-links between different commodities, as well as volatility persistence. Although gold and silver have had more attention than our other two precious metals³ (platinum and palladium), research studies on oil price fluctuations are common in the literature.

Pindyck and Rotenberg (1990)⁴ are the pioneers on the study of excess co-movement for unrelated commodities including gold, silver and oil. Their findings show that after accounting for similar economic fundamentals, a group of unrelated raw commodity prices tend to move together. Palaskas and Varangis (1991), Trivedi (1995) and Deb et al. (1996) also researched on erratic co-movement in the prices of commodities using different time series techniques and found less excess co-movement amongst unrelated commodity prices. Nevertheless, Cashin et al., (1999)

³ Adeniyi et al. (2012), Aliyu S.U. R., (2009), Batten et al., (2010), Morales, L. & Adreosso-O'Collaghan, B., (2012) are a few of many that have researched on oil price fluctuations.

⁴ Trivedi (1995) and Deb et al. (1996) have also written on commodity price movements.

sturdily deny that unrelated commodity prices move together. After using concordance econometrics techniques on dissimilar commodities under similar macroeconomic conditions, they contended that the Pindyck and Rotenberg (1990) finding was a “fairytale”. Others like Marquis and Cunningham (1990), Hua (1998) and Awokuse and Yang (2003) had findings that supported those of Cashin et al., (1999). In this thesis, instead of randomly selected commodities, our focus is on selected related commodities unlike a mix of both related and unrelated commodities.

Fluctuating price returns of metals and the rampant swings in oil prices have kept traders, investors and other market participants on perpetual alert especially during periods plagued with rising uncertainty in the markets. Levin and Wright (2006) suggest that gold is an effective long-run inflationary hedge asset since its short run price fluctuates steadily with increases in the overall rate of inflation, and that short-run factors impact on nominal gold prices. In their examination whether gold is a good diversifier of a sanctuary during crises, Baur and Lucey (2010) used stock and bond markets data for the United States, United Kingdom and Germany. They established that in the short-run, gold is a “*safe haven*” for stocks in all the above markets after which gold investments become unsafe especially after an adverse shock. They postulate that after 15 trading days, investors will realize depreciation in both their gold holdings and gold investments. Throop (1993), Zhou (1995), Dibooglu (1995) amongst others, suggest that there exists a positive relationship between oil prices and the dollar exchange rate. While Amano and Van Norden (1995) investigate the causal relationship between these variables, they find that oil price essentially affect the long-term dollar exchange rate in Japan, Germany and the

U.S.⁵ Sari et al. (2009) propose that investors usually skip from oil to gold, and vice versa, or a mixture of investments having both commodities during inflationary periods in a bid to minimize their losses given the close relationship between the commodities. In addition, they postulate that silver can act as a leveraged asset on gold. This pushes investors to purchase silver prior to gold when gold prices are rising, and sell gold prior to silver when gold prices are falling as a loss minimization strategy. As opposed to most other research on commodity prices, our emphasis is on selected precious metal price transmission dynamics. We aim to abate the inherent information diffusion that is prominent when a cluster of heterogeneous commodities are used while accounting for the impact of the recent global financial crises.

If investors are considering precious metal investments, then it would be relevant to know whether their returns will be substantial and/or less risky than those of traditional investments. Therefore some concerns have been evident whether higher returns would be generated when investment in precious metals is done through physical (e.g. gold bullions etc.) or as soft assets (i.e. shares of gold mines etc.). The study by Conover, Jensen, Johnson & Mercer (2007) concludes that, investing indirectly in precious metals through commodities rather than in the physical assets yields a higher return in spite the fact that gold (silver) offers the highest (lowest) marginal returns. They reiterate that this boost in investment return is in conjunction with the Federal Reserve Bank (FED) operating a loose rather than tight monetary policy. Their results complement the fact that tight monetary policies frequently coincide with periods of high expected and actual inflation while taking cognizance of the hedge properties of precious metals.

⁵ See Benassy Quere et al., (2007)

The dollar-euro exchange rates may trigger changes in oil and the precious metals prices and vice versa since it fundamentally links these commodities in global exchanges. On the relationship between oil and the real exchange rates, Amano and van Norden (1998) conclude that on the most part, oil price usually overrides. It should be noted that the persistent and time-varying co-movements of commodity prices with oil prices and exchange rates are of great interest to investors who consider making important investment decisions in asset classes. Price movements of commodities are vital in subverting foreign exchange earnings especially in developing countries. This is critical because for these countries, commodities like gold and silver are often used as substitutes for the U.S. dollar particularly during recessions. Therefore, depreciation of the dollar as seen in recent years has triggered a surge in the demand for these commodities⁶, thereby driving their prices up. Given that these commodities are widely traded in US dollars, the historical changes in the prices of commodities like gold, oil and copper have been known to adequately forecast the direction of the U.S. economy (Coudert et al., 2007).

Unlike others, this study contributes to the literature by investigating these precious metal price drivers, and whether their relationship lingers pre and post financial crisis. We use the Johansen test for cointegration and the Vector Error Correction Model (VECM) to unravel the short and long term relationship amongst these precious metals as well as the Markov switching (MS-VEC) to analyze the price movements in multiple latent regimes. Finally using two Generalized Autoregressive Conditional Heteroscedastic (GARCH) Models, we analyze volatility persistence and convergence as well as the presence of leverage effect of these precious metals.

⁶ Gold and silver are usually considered “*safe haven*” commodities because their inherent values are supposedly unchanged during severe economic circumstances.

On the literature regarding nonlinearity and chaotic phenomena, Soni (2013) used the AR (p)-GARCH (1, 1) model to investigate nonlinearity in serial dependence for the Indian commodity market. This author concludes by confirming the presence of nonlinearities in the series. Barkoulas et al. (2012) examine whether stochastic or deterministic endogenous trends guided the fluctuations in crude oil spot prices. They use both metric and topographic diagnostic tools and found that stochastic rules explained these spot market forces.

Not many studies have examined precious metal price volatility transmissions using a flexible form of the Bayesian MS-VEC model that allows both the coefficients and variances to change based on the prevailing regime, as we do in this thesis. Djuric et al. (2012) and Listorti and Esposti (2012) are some of the few studies that use the MS-VEC model to study commodity prices. The previous studies that used the MS-VEC model approach neither used our four selected precious metals, nor did they develop regime-dependent impulse responses to analyze the impact and magnitude of spontaneous shocks in different regimes as we do.

Our study also differs from others in that apart from focusing related commodities, we consider a more realistic multi-state environment thus adding to the literature by studying the price transmission mechanism between related precious metal spot prices, oil and exchange rate. We therefore do not undermine the potential for information diffusion inherent when a cluster of heterogeneous commodities are used. In addition, a single state economy is unrealistic given that the states of the economy are dynamic rather than static. Given that the selected commodities are related and the economy is observed to be dynamic and the coefficients under each regime are time-varying, we therefore effectively capture the magnitude and impact

of the price dynamics in different states of the economy, thereby presenting a more realistic picture. We use high frequency, broad and long data set which includes periods of great economic dynamism, hence enabling our series to provide more realistic and updated results.

Considering the literature on commodity price volatility, there have been numerous studies on commodity price volatility and efficiency in commodity markets. Oil price volatility has literally dominated this brand of research relative to other crude commodity prices (Reignier, 2007). Hammoudeh et al., (2004) investigated volatility persistence in the crude oil market and oil equity markets using both univariate and multivariate GARCH models. Their findings suggest that after oil, gold has attracted the most attention relative to other commodities. Using intraday and interday data, Batten and Lucey (2007) examined gold futures contracts traded on the Chicago Board of Trade (CBOT). They provided an interesting perception in the intraday and interday volatility changes of gold by examining the behavior of the futures returns and the other nonparametric Garman-Klass volatility range statistic (Garman and Klass, 1980).

Furthermore, using both univariate and bivariate GARCH models, Ewing and Malik (2013) employed univariate and bivariate GARCH models to examine the instability of gold and oil futures. While accounting for structural breaks, they highlighted their findings by computing peak portfolio weights and dynamic low risk hedge ratios. Hammoudeh et al., (2009) found the existence of a non-linear relationship, the presence of short and long run dependency and interdependency of both news and past volatilities in their study on precious metal volatility. The Ican-Tiao algorithm and the GARCH model were used by Wilson et al. (1996) to compare unexpected

changes in variance and volatility persistence in crude oil. O'Callaghan and Morales (2011) examine volatility persistence with data from three world major stock equity index (Dow Jones Industrials, FTSE 100, and Nikkei 225) on precious metals returns and oil returns. They checked the robustness of precious metals returns in light of the 2007/2008 mortgage crisis and their findings provided a fresh direction on how investors should invest in precious metals. Tully and Lucey (2007) accounted for leverage effect by nested ARCH and GARCH models in an APGARCH model. Their results confirm that the U.S. dollar may be the core; or the unique variable affecting gold price fluctuations and persistence when looking at abrupt fluctuations in the variance of gold and the other precious metals. Batten et al., (2010) find that macroeconomic factors like financial market sentiments, monetary policy and business cycles affect volatility of gold, silver, platinum and palladium differently. They found gold to be greatly influence by exchange rate changes and inflation, thence making it the best windbreak for inflationary pressures and exchange rate variations. Platinum and palladium apparently can be good financial market instrument than gold. Actually, Hammoudeh, Malik and McAleer (2011) proposed that expected future risks can be mitigated by including gold in optimal precious metal portfolios. Although we do not investigate optimal portfolio weights for precious metal investments, we probe volatility convergence in relation to precious metals while accounting for oil and exchange rate variations. We also verify the effect of asymmetric information on the returns.

The following points highlight the major contributions of this thesis to the current literature on commodity price movements. This study differs from others in that, the fact that our choice variables are related precious metals circumvent the potential for information diffusion between related and unrelated commodities. Other studies

focus on unrelated and related commodities, or on agricultural and/or industrial goods. With related commodities, we overcome the information diffusion problem inherent when a cluster of heterogeneous commodities are used.

Moreover, this study ignores the unrealistic one state economy considered by most previous studies and takes cognizance of a two state dynamic and more realistic economy rather than a static economy. Our selected commodities are related and the economy is observed to be dynamic and also the coefficients under each regime are time-varying. This allows us to effectively capture the magnitude and impact of the price dynamics in different states of the economy, thereby presenting a more realistic picture. We also use fairly extensive, high frequency and broad data set which includes periods of great economic dynamism, hence rendering our series to provide more robust and updated results. Our findings are more vigorous given that we consider the AFC and GFC that dramatically influence expectations and thus investors' decision on including alternative precious metals in their portfolios for diversification reasons.

Chapter 3

INFORMATION TRANSMISSION IN OIL PRICES, PRECIOUS METALS PRICES AND EXCHANGE RATES

3.1 Introduction

It goes without saying that in the last few decades, the rise and fall in precious metal prices have hatched substantial interest in global financial markets. As mentioned earlier, the expanding uses of precious metals in art, jewelry, medicine, investments and as investment assets have attracted many international investors. In addition, the price co-movement provides precedence for smart investors to benefit from the possible reasons for such synchronized movements when exposed to similar macroeconomic conditions. Under this assumption of commodity price co-movement, few studies have unveiled which are the precious metal drivers or leaders, or the direction of movements and their relationship to variables like oil and exchange rates. Historically, although gold has led the group, silver sometimes has outperformed gold. Platinum is almost always in lock-up with gold while palladium and platinum sometimes are closely linked to silver.

The dollar exchange rate can also trigger both precious metals and oil price movements since trade in oil is denominated in US dollars. It is also well known that investors switch between dollar-valued soft assets to dollar-valued physical assets

particularly during crises periods. However, recent experience has shown that when the dollar weakens with regard to the euro, the price of oil significantly rise significantly since oil is principally traded in dollars. Amano and Van Norden (1998) amongst others suggest that real oil price is dominant when oil prices and exchange rates are considered in real rather than nominal terms. In fact, the dollar and euro represent the lubricant in international exchanges for not only oil, but also for precious metals and other commodities. Therefore this section examines the short and long run relationship between these precious metal prices, oil and the dollar-euro exchange rates. The next section is an extension of this section which will provide information on whether some of our commodities can be a safe haven or a hedge asset. A hedge asset is one that is uncorrelated (or negatively correlated) with stocks or bonds but on average, not essentially only during a crash while a safe haven⁷ is an asset having low correlation with other assets. Gold and palladium sometimes exhibit such properties. Hence we probe whether or not the linkage between these precious metal prices stayed same over the sample period.

3.2 Data and Descriptive Statistics

3.2.1 Data

The sample contains daily closing spot prices of the four precious metals, the oil spot prices and the dollar/euro exchange rate. It covers a five-working day week from January 1987 to February 2012, thus spanning a 25-year time period. The data was obtained from DataStream International - Thompson Reuters. The exchange rate represents the value of the US dollar per euro. Hence rising (falling) exchange rate, it signifies depreciation (appreciation) of the dollar against the euro. The exchange rate represents a major linkage between these commodities since producers and

⁷ See Davidson et al., (2003) for the diversification and safe haven properties of gold

consumers use both currencies to trade in these commodities globally. Moreover deterioration of the dollar against the euro raises these commodity prices especially oil prices which are also priced in US dollars. The hallmark for the crude oil spot price is the West Texas Intermediate (WTI) and is quoted in US dollars/barrel. Gold, silver,⁸ platinum and palladium all trade in the Commodity Exchange Inc. (COMEX) and valued in US dollars/troy ounce. Daily spot returns was constructed from the spot price data as $\log (P_{s,t}/P_{s,t-1})$ where $P_{s,t}$ stands for each commodity price or exchange rate at time t and $P_{s,t-1}$ is the previous period's spot price or exchange rate. The entire data series are expressed in natural logarithms. Time series plots of the log levels of the series are given in Figure 1.

The period of this study reflects times of major shocks such as the dot-com boom of the early 2000's and the housing market bubble of 2007. It is characterized by high commodity price volatility, increasing integration by emerging market in global trade, and an era of high risk aversion in the financial markets. As seen on the figure, from the early 90's to the year 2000 the prices seemed stable before a steep drop in the year 2000. Thereafter, the price trend of the commodities all heightened till the global recession. Descriptive statistics in both level and log-level form are found on Tables 1-A and 1-B respectively.

⁸ Silver price is quoted in cents per troy ounce in the COMEX but for consistency, we transformed it to US dollars per troy ounce.

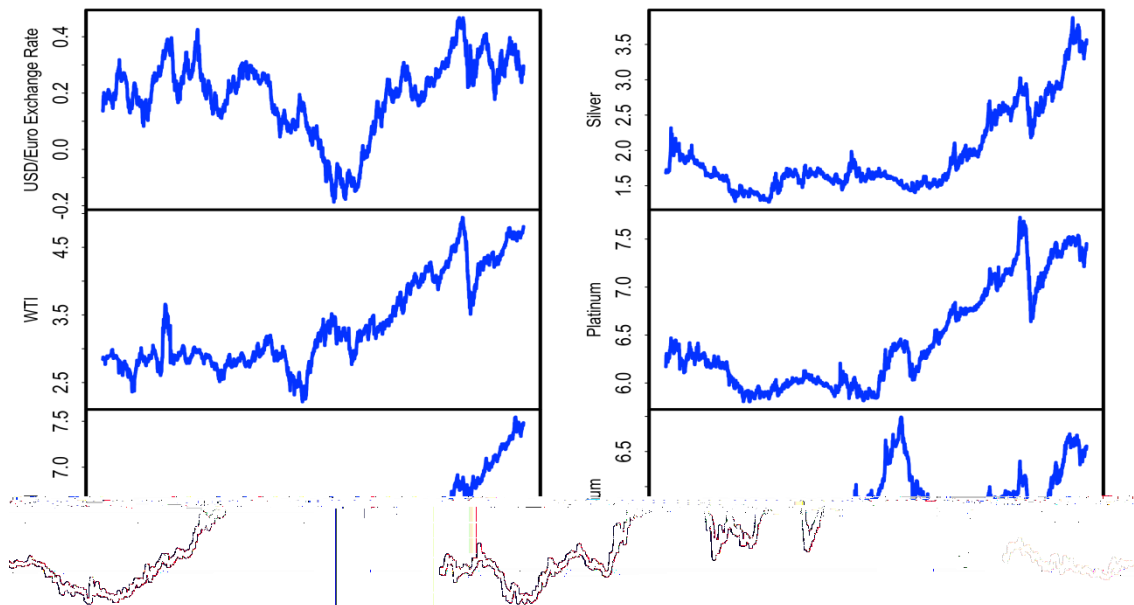


Figure 1: Exchange Rate, Oil, Gold, Silver, Platinum, and Palladium Price Data

Note: Figure 1 plots the logarithm of the US dollar/euro exchange rate, West Texas Intermediate (WTI) crude oil price, gold price, silver price, platinum price, and palladium price. The sample period covers 5/1/1987-17/2/2012 with 6560 observations.

3.2.2 Descriptive Statistics

From the Table 1, it is seen that among the five commodities, gold and platinum have the lowest historical price volatility as viewed by their standard deviations (0.475 and 0.526, respectively). Gold has been used as a long run inflationary hedge due to its monetary value. In addition, large quantities of gold are being hoarded, while much of the gold supply comes from recycling. All these factors account for the low historical volatility of gold.

It can be seen that oil and palladium have the highest standard deviations (0.660 and 0.632, respectively) in the group. This may be due to oil being a major energy source and being heavily used as an input in production of many other commodities. For platinum, the low volatility may be due to its substantially lower industrial use. Our

results are concurrent to those of Hammoudeh et al. (2009). From Table 1, oil has the highest historical daily mean return (0.030%), followed by silver, palladium, gold, and platinum, respectively. The estimates of the Ljung-Box autocorrelation tests indicate that the levels and returns of all series are strongly autocorrelated except gold and silver returns which are weakly correlated.

Table 1: Descriptive Statistics

	ER	WTI	GOLD	SILV	PLAT	PALL
<i>Panel A: log levels</i>						
Mean	0.193	3.338	6.116	1.939	6.442	5.413
S.D.	0.134	0.660	0.475	0.574	0.526	0.632
Min	-0.188	2.212	5.533	1.266	5.801	4.360
Max	0.469	4.947	7.549	3.883	7.729	6.994
Skewness	-0.787	0.739	1.301	1.379	0.746	0.405
Kurtosis	0.297	-0.701	0.748	1.039	-0.776	-0.794
JB	700.992***	730.717***	2006.279***	2377.588***	772.544***	351.652***
Q(1)	6547.694***	6551.660***	6551.921***	6548.551***	6554.303***	6551.957***
Q(4)	26103.191***	26136.583***	26147.678***	26113.980***	26173.713***	26146.327***
ARCH(1)	6531.685***	6544.571***	6552.933***	6546.271***	6541.866***	6538.564***
ARCH(4)	6528.719***	6541.962***	6549.939***	6543.493***	6538.884***	6535.631***
<i>Panel B: log returns</i>						
Mean	0.002%	0.030%	0.023%	0.029%	0.020%	0.027%
S.D.	0.632%	1.958%	0.967%	1.761%	1.417%	2.014%
Min	-3.844%	-42.986%	-7.218%	-23.672%	-17.277%	-17.859%
Max	4.617%	17.267%	7.382%	13.665%	11.728%	15.841%
Skewness	0.072%	-1.736%	-0.266%	-0.797%	-0.704%	-0.174%
Kurtosis	2.384%	41.323%	7.104%	11.090%	9.595%	7.074%
JB	1560.7640***	470270.5990***	13880.5480***	34333.9760***	25719.9350***	13718.8920***
Q(1)	3.1293*	150.4286***	0.1315	2.4898	2.554	9.7048***
Q(4)	7.5855	168.8500***	2.3055	5.4063	13.1438**	19.0882***
ARCH(1)	35.0174***	85.8749***	173.4158***	197.1089***	199.0196***	187.1028***
ARCH(4)	219.0870***	177.7399***	350.2809***	322.3383***	331.5975***	427.0109***
<i>n</i>	6560	6560	6560	6560	6560	6560

Note: All values are in natural logarithms in Panel A. Panel B gives the descriptive statistics for log returns. The sample period covers 5/1/1987-17/2/2012 with $n=6560$ observations. ER stands for US Dollar/Euro exchange rate, WTI for West Texas Intermediate crude oil price, GOLD for gold price, SILV for silver price, PLAT for platinum price, and PALL for palladium price. In addition to the mean, standard deviation (S.D.), minimum (min), maximum (max), skewness, and kurtosis statistics, the table reports the Jarque-Berra normality test (JB), the Ljung-Box first [$Q(1)$] and the fourth [$Q(4)$] autocorrelation tests, and the first [ARCH(1)] and the fourth [ARCH(4)] order Lagrange multiplier (LM) tests for the autoregressive conditional heteroskedasticity (ARCH). ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

The autoregressive conditional heteroscedasticity (ARCH) tests for all series indicate strong ARCH effects. Moreover, normality is rejected at the 1 percent level for all

series. Autocorrelation motivates the use of dynamic models, while the ARCH effect and non-normality underscore the importance of the utilization of nonlinear models.

The correlation matrix in Table 2 shows that gold and silver have the highest positive historical correlation in the group (95%). This may be explained not only by the monetary features possessed by both metals, but also by their extensive uses as investment assets, and as industrial commodities used in the jewelry and medical industries.

Table 2: Correlation Matrix for the Levels and for the Returns (Full Sample)

	ER	WTI	GOLD	SILV	PLAT	PALL
--	----	-----	------	------	------	------

Panel A: log levels

ER	1.000					
WTI	0.419	1.000				
GOLD	0.639	0.831	1.000			
SILV	0.498	0.853	0.953	1.000		
PLAT	0.412	0.941	0.865	0.905	1.000	
PALL	-0.294	0.595	0.384	0.575	0.609	1.000

Panel B: log returns

ER	1.000					
WTI	0.064	1.000				
GOLD	0.289	0.167	1.000			
SILV	0.239	0.162	0.625	1.000		
PLAT	0.184	0.143	0.437	0.400	1.000	
PALL	0.169	0.097	0.318	0.307	0.566	1.000

Note: Table reports the pairwise Pearson correlation coefficients for log levels (Panel A) and log returns (Panel B) of the series. See note to Table 1 for variable definitions.

The high historical correlation between platinum and oil (94%) may be due to their joint industrial uses, particularly in the automobile industry. Due to its forward and

backward linkages in several sectors and its use as a resource currency, oil has the highest historical correlation with all other precious metals in the group. The lowest historical correlation of palladium with all of the other commodities explains why traders and institutional investors in precious metals include palladium in their investment portfolios as a hedge asset.

Table 3 shows the correlation matrix for the period prior and post 2007/2008 financial crisis. Gold and silver maintain their high positive historical correlation in periods before and after the crisis for reasons already mentioned above. Post crisis, palladium has the highest correlation with all the other commodities. The persistent high platinum-palladium correlation both pre and post crisis may be due to their substitute nature and persistent demand in the automobile industry for making catalytic converters. This behavior of palladium presents different features that may present diversification options for precious metal investors. Oil maintains relatively high returns correlation with the other commodities post crisis as expected.

Table 3: Correlation Matrix before and after crisis

<i>Before Crisis</i>	LWTI	LGOLD	LSILV	LPLAT	LPALL	LER
LWTI	1					
LGOLD	0.61	1				
LSILV	0.67	0.83	1			
LPLAT	0.88	0.71	0.83	1		
LPALL	0.4	-0.18	0.29	0.42	1	
LER	0.13	0.66	0.29	0.12	-0.69	1
<i>After Crisis</i>						
LWTI	1					
LGOLD	0.52	1				
LSILV	0.7	0.93	1			
LPLAT	0.82	0.5	0.68	1		
LPALL	0.77	0.85	0.92	0.83	1	
LER	0.48	-0.21	0.05	0.43	0.06	1

Note: L stands for the log operator, WTI, SILV, PLAT, PALL and ER stand for oil, silver, platinum, palladium and exchange rates respectively

3.3 Empirical Methodology

3.3.1 Stationarity Tests

To ascertain the relationship between the selected precious metals in the presence of oil and exchange rate shocks, we begin by examining the time series properties of our data to determine stationarity. The Augmented Dickey and Fuller (ADF) tests (1979) and Phillips-Perron (PP) tests (1988) are initially conducted. To eliminate the shortfalls of the ADF and PP tests, more reliable tests were performed like the Dickey-Fuller GLS detrended (DF-GLS), Kwiatkowski et al. (1992) (KPSS), and Ng and Peron's MZ α (NPZ α) tests. The appropriate lag length for the above tests is selected based on the modified Bayesian Information Criterion (BIC). In levels, the variables are non-stationary but become stationary when first differenced. Table 4 summarizes the results of the unit root test. With the first difference of the variables being stationary, we proceed to determine the long run relationship amongst the variables by performing co-integration tests.

3.3.2 Johansen Cointegration Test

The presence of a long run relationship between these selected commodity prices and exchange rates is tested by using the well-known Johansen (1995) test for co-integration. Standard co-integration theory suggests that, if two or more non-stationary series have the same stochastic trend, then implicitly, they will tend to move together in the long run (Engel and Granger (1987)). Notwithstanding, there can be divergence from the long run equilibrium in the series in the short run. The unit root test results reveal that all the series are integrated of same order I (1); thus affirming the appropriateness of this test. The Johansen Co-integration test can be conducted through a k^{th} order vector error correction model (VECM) represented by:

$$\Delta X_t = \mu_t + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-k} + \varepsilon_t \quad (1)$$

Where X_t is an $n \times 1$ vector to be investigated for co-integration, ΔX_t is a vector of difference deterministic terms, μ_t is the vector of intercepts, while Π is the long-run coefficient and Γ is the short coefficient matrices to be determined. Π can be decomposed into two $n \times r$ matrices α and β such that $(\Pi = \alpha\beta')$, with β being the matrix of co-integrating vectors and α is the adjustment parameter in the VEC model. The lag length k is selected based on the Akaike Information Criterion (AIC). If there is co-integration within the series, the number of co-integrating vectors is selected based on the rank of the co-integrating matrix Π . If the rank of the matrix Π is zero, then there will be no co-integration, while if the full rank of the variable exists, then the variable X_t will be stationary. However, if the rank lies between zero and p , then there is co-integration between the variables. Two likelihood ratio (LR) tests (λ_{\max} test and trace test) are used to verify the existence of co-integration or the long run relationship between the variable. The null hypothesis of at most r co-integrated variables against the alternative of more than r co-integrating vectors is tested by the trace statistics given by:

$$\lambda_{\text{trace}} = -T^* \sum_{i=r+1}^p \ln(1 - \lambda_i) \quad (2)$$

where T is the number of observation and λ is the eigen values. Additionally, the null hypothesis of the trace test is $(p-r)$ co-integrating vectors. The trace test is considered since it provided a more consistent way of determining the co-integration rank (Johansen, 1992; Johansen and Juselius 1992). The Maximum Eigen value statistic as given below as:

$$\lambda_{\max} = -T \ln(1 - \lambda_{r+1}) \quad (3)$$

where, λ_i 's are the eigen values of the vectors $\Pi=\alpha\beta'$. The notion behind the λ_{\max} test is that if the $(r+1)^{\text{th}}$ eigen values is accepted to be zero, then the smaller eigen values must also be zero. The Johansen (1995) Test for co-integration is preferred in this case over the Bounds test (Pesaran and Pesaran, 1996) because the sample data is very broad, and the test is more flexible and can be applied to higher series i.e. I(2) provided the series are integrated of same order. Moreover, the bounds test is effectiveness for small sample tests (which precludes our sample data). In addition, all series must be I (1) for the Bounds test to yield reliable inference (Sari et al., 2009). The results of the maximum eigen value and trace statistics indicate that the log series are I (1). We reject the null hypothesis of rank = 0 and cannot reject the alternative hypothesis of rank =1 at a 5% level. The co-integration estimates are presented in Table 4. In addition to the Johansen (1995) test, the Stock and Watson (1988) multivariate test was also applied. Generally the test posits that if we have m co-integrated I (1) series with a co-integrated rank $r < m$, then these series have $m-r$ stochastic trend. Under the null hypothesis, k common stochastic trends are tested against $k-r$ stochastic trend (or co-integration relationships). Panel C of Table 5 presents the results of the Stock-Watson co-integration test.

3.3 Empirical Results and Discussion

In levels, the ADF and PP test indicate non-stationarity but when first differenced, the stock returns become stationary. Engle and Granger (1987) emphasized the significance of using the first difference or level form of the data in running the analysis. This is crucial since there is a high risk of incorrectly specifying the model if the wrong structural representation of the model is applied when testing for the

Table 4: Unit Root Tests

	ADF	DF-GLS	PP	KPSS	NP- Z_α
<i>Panel A: Level</i>					
<i>Deterministic regressors in the test equation: Constant</i>					
ER	-1.849 [0]	-1.598 [0]	-1.903	1.501 ^{***}	-5.645 [0]
WTI	1.668 [0]	2.094 ^{**} [0]	1.667	5.212 ^{***}	3.345 [0]
GOLD	-0.896 [1]	0.110 [1]	-0.886	6.069 ^{***}	0.209 [1]
SILV	-0.318 [0]	0.230 [0]	-0.238	7.609 ^{***}	0.446 [0]
PLAT	0.340 [0]	0.844 [0]	0.312	6.049 ^{***}	1.922 [0]
PALL	-0.476 [2]	0.296 [2]	-0.452	7.913 ^{***}	0.623 [2]
<i>Deterministic regressors in the test equation: Constant and linear trend</i>					
ER	-1.882 [0]	-1.889 [*] [0]	-1.936	1.443 ^{***}	-7.203 [0]
WTI	-0.099 [0]	0.137 [0]	-0.112	2.289 ^{***}	0.249 [0]
GOLD	-1.969 [1]	-1.886 [*] [1]	-1.944	0.510 ^{***}	-7.417 [1]
SILV	-2.024 [0]	-1.291 [0]	-1.944	2.042 ^{***}	-3.798 [0]
PLAT	-1.223 [0]	-0.868 [0]	-1.247	1.929 ^{***}	-2.598 [0]
PALL	-2.452 [2]	-1.788 [*] [2]	-2.418	1.673 ^{***}	-7.264 [2]
<i>Panel B: First differences</i>					
<i>Deterministic regressors in the test equation: Constant</i>					
ER	-79.202 ^{***} [0]	-6.011 ^{***} [23]	-79.200 ^{***}	0.0705	-21.626 ^{***} [23]
WTI	-81.333 ^{***} [0]	-8.085 ^{***} [19]	-81.333 ^{***}	0.874 [*]	-37.534 ^{***} [19]
GOLD	-77.916 ^{***} [0]	-2.860 ^{***} [30]	-77.881 ^{***}	0.0876	-7.261 [*] [30]
SILV	-60.178 ^{***} [1]	-2.544 ^{**} [20]	-82.669 ^{***}	0.1936	-7.901 [*] [20]
PLAT	-79.466 ^{***} [0]	-10.366 ^{***} [19]	-79.456 ^{***}	0.313	-54.519 ^{**} [19]
PALL	-56.070 ^{***} [1]	-14.786 ^{***} [14]	-68.956 ^{***}	0.123	-166.649 ^{***} [14]
<i>Deterministic regressors in the test equation: Constant and linear trend</i>					
ER	-79.196 ^{***} [0]	-10.736 ^{***} [16]	-79.195 ^{***}	0.063	-66.858 ^{***} [16]
WTI	-81.421 ^{***} [0]	-21.044 ^{***} [8]	-81.421 ^{***}	0.068	-518.245 ^{***} [8]
GOLD	-77.914 ^{***} [0]	-8.379 ^{***} [17]	-77.878 ^{***}	0.070	-43.221 ^{**} [17]
SILV	-60.192 ^{***} [1]	-5.240 ^{***} [18]	-82.681 ^{***}	0.034	-21.474 ^{**} [18]
PLAT	-79.493 ^{***} [0]	-77.224 ^{***} [0]	-79.481 ^{***}	0.027	-3271.640 ^{***} [0]
PALL	-56.079 ^{***} [1]	-54.780 ^{***} [1]	-68.950 ^{***}	0.020	-3503.940 ^{***} [1]

Note: Panel A reports unit roots tests for the log levels of the series. Panel B report unit root test for the first differences of the log series. ADF is the augmented Dickey-Fuller (Dickey and Fuller, 1979) test, PP is the Phillips-Perron unit root test (Phillips and Perron, 1988), NP- Z_α is the modified Phillips-Perron tests of Perron and Ng (1996), DF-GLS is the augmented Dickey Fuller test of Elliot et al. (1996) with generalized least squares (GLS) detrending, and KPSS is the Kwiatkowski et al. (1992) stationarity. PP and NP- Z_α tests are based on GLS detrending. For the ADF unit root statistic the lag order is selected by sequentially testing the significance of the last lag at 10% significance level. The bandwidth or the lag order for the PP, NP- Z_α , DF-GLS, and KPSS tests are select using the modified Bayesian Information

Criterion (BIC)-based data dependent method of Ng and Perron (2001). ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Multivariate Cointegration Tests

Panel A: VAR order selection criteria

Lag (p)	1	2	3	4	6	7	8
AIC	-52.957	-53.031	-53.034	-53.032	-53.031	-53.031	-53.029
HQ	-52.942	-53.003	-52.993	-52.979	-52.964	-52.951	-52.937
BIC	-52.913	-52.950	-52.916	-52.877	-52.838	-52.801	-52.762

Panel B: Johansen cointegration tests

Eigenvalues	0.0067	0.0034	0.0032	0.0018	0.0005	0.0001	
		Critical values				Cointegration vector	
H_0	λ_{\max}	10%	5%	1%	ER	1.0000	
$r = 5$	0.720	6.500	8.180	11.650	WTI	-0.3985	
$r = 4$	3.530	12.910	14.900	19.190	GOLD	0.2720	
$r = 3$	11.960	18.900	21.070	25.750	SILV	-0.4656	
$r = 2$	21.340	24.780	27.140	32.140	PLAT	0.4030	
$r = 1$	22.410	30.840	33.320	38.780	PALL	0.2839	
$r = 0$	44.040**	36.250	39.430	44.590	ER	1.0000	
						Loadings	
H_0	λ_{trace}	10%	5%	1%	ER	-0.0020	
$r \leq 5$	0.720	6.500	8.180	11.650	WTI	0.0120	
$r \leq 4$	4.260	15.660	17.950	23.520	GOLD	-0.0030	
$r \leq 3$	16.220	28.710	31.520	37.220	SILV	-0.0001	
$r \leq 2$	37.560	45.230	48.280	55.430	PLAT	-0.0029	
$r \leq 1$	59.980	66.490	70.600	78.870	PALL	-0.0063	
$r = 0$	104.020**	85.180	90.390	104.200			

Panel C: Stock-Watson cointegration test

$H_0: q(k, k-r)$	Statistic	Critical values: $q(6,5)$ $q(6,4)$		
$q(6,0)$	2.181	1%	-60.20	-38.20
$q(6,1)$	-4.193	5%	-49.80	-31.50
$q(6,2)$	-4.193	10%	-44.80	-28.30
$q(6,3)$	-30.848			
$q(6,4)$	-30.848*			
$q(6,5)$	-74.689***			

Note: The table reports selection criteria and multivariate cointegration tests for the VAR (p) model of the six variables. Panel A reports the AIC, BIC, and Hannan-Quinn (HQ) information criteria. The VAR order is selected based on minimum BIC and is 2. Panel B reports maximal eigenvalue (λ_{\max}) and trace (λ_{trace}) cointegration order tests of Johansen (1988, 1991). Non-rejection of $r=0$ for the Johansen tests implies no cointegration. Panel C reports the multivariate cointegration test of Stock and Watson (1988). Under the null $q(k, k-r)$ of Stock-Watson cointegration test, k common stochastic trend is tested against $k-r$ common stochastic trend (or r cointegration relationship). Rejection of $q(6, 5)$ for the Stock-Watson test implies

cointegration. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

long run relationship between the variables under investigation. The stationarity results are summarized in Table 4.

All five deterministic trend models of Johansen (1995) were employed to ascertain the long-run relationship amongst the variables. The maximum eigen value test and trace statistics showed at least one co-integration vector implying that the variables in our series are first order integrated i.e. I(1). The Stook-Watson test results on Panel C of Table 5 also concur with the Johansen (1995) test results. Having found the cointegration relationship between the variables, we fit the error correction model in the system. The VECM is appropriate for the analysis because, each of the variables in the series is I(1) i.e. first order integrated implying that the variables follows a random walk but eventually become stationary after first differencing. This also implies that as the variables are cointegrated, there exists a linear combination of the variables that is stationary.

Table 6 shows the parameter estimates of the error correction model with the coefficient of the variables and standard errors in parenthesis. Significance of the variables at 1%, 5% and 10% levels are represented by ***, ** and * respectively. Panel A on the table shows the long run cointegrating coefficient (β') and the adjustment coefficient (α). As expected, gold takes a much longer period to adjust to its long run equilibrium value relative to silver. Although palladium and platinum derive much of their demand from similar sectors of the economy, palladium appears to adjust much faster than platinum. Panel B on the table show all the long run parameter estimates for the variables. The speed of adjustment parameters represents

overshooting parameters which indicates how quickly the system adjusts to its long run equilibrium. Generally, we conjecture the speeds of adjustments to be negative because commodity prices must fall to re-establish the long-run equilibrium among the system variables.

Table 6: Parameter Estimates for the Error Correction Model for Oil, Gold, Silver, Platinum, Palladium and Exchange Rates.

<i>Panel A:</i> Cointegrating Vector (β') and Adjustment Coefficients (α)						
	LWTI	LGOLD	LSILV	LPLAT	LPALL	LER
	1.000	-0.886246	1.368268	-1.019304	-0.747285	-2.45245
	-0.00413	0.001165	-0.000538	0.000871	0.002387	0.000753

<i>Panel B:</i> Parameter Estimates ($\pi = \alpha\beta'$)							
	Constant	Δ LWTIt-1	Δ LGOLDt-1	Δ LSILVt-1	Δ LPLATt-1	Δ LPALLt-1	Δ LERt-1
LWTI	10.1389	1.000	-0.799	1.319	-0.995	-0.779	-2.713
LGOLD	-12.6932	-1.252	1.000	-1.651	1.246	0.975	3.396
LSILV	7.6865	0.758	-0.606	1.000	-0.754	-0.590	-2.057
LPLAT	-10.1894	-1.005	0.803	-1.326	1.000	0.782	2.726
LPALL	-13.0220	-1.284	1.026	-1.674	1.278	1.000	3.484
LER	-3.7373	-0.369	0.294	-0.486	0.367	0.287	1.000

<i>Panel C:</i> Short-run Parameter Estimates						
Variables/ Equation	Δ LWTI	Δ LGOLD	Δ LSILV	Δ LPLAT	Δ LPALL	Δ LER
Constant	0.00025 (0.00024)	0.00023 (0.00012)*	0.00028 (0.00022)	0.00016 (0.00017)	0.00025 (0.00025)	0.0000238 (0.0000778)
Δ LWTIt-1	0.15243 (0.01254)***	0.01224 (0.00626)*	0.01967 (0.01146)*	0.02935 (0.00904)***	0.02627 (0.01294)*	-0.00886 (0.041)**
Δ LGOLDt-1	0.01864 (0.03334)	-0.08911 (-0.01664)***	-0.01658 (0.03046)	0.04091 (0.02404)*	-0.00361 (0.03439)	-0.01814 (0.01091)*
Δ LSILVt-1	0.05855 (0.01781)**	0.06837 (0.00889)***	0.01259 (0.01627)	0.1292 (0.01284)***	0.17894 (0.018237)***	0.02243 (0.00583)
Δ LPLATt-1	0.0207 (0.02201)	-0.00862 (0.01098)	0.00346 (0.0201)	-0.13658 (0.01587)***	-0.11119 (0.0227)***	-0.0013 (0.0072)
Δ LPALLt-1	-0.02414 (0.0145)	0.00223 (0.00724)	0.02093 (0.01325)	0.04396 (0.01045)***	0.0376 (0.01495)**	-0.01074 (0.0047)**
Δ LERt-1	-0.00503 (0.03968)	0.04965 (0.01980)**	0.02082 (0.03626)	0.03796 (0.02861)	0.03531 (0.04093)	0.02537 (0.01299)*
Δ LWTIt-2	-0.06063 (0.01253)***	-0.00223 (0.00625)	-0.1228 (0.01145)	0.00153 (0.00904)***	0.00023 (0.01292)	0.00351 (0.0041)
Δ LGOLDt-2	0.00415 (0.03333)	0.02829 (0.01663)*	0.05559 (0.03046)*	-0.01022 (0.02303)	-0.0259 (0.03438)	0.0254 (0.01091)**
Δ LSILVt-2	-0.02449 (0.01799)	-0.01927 (0.00898)**	-0.01496 (0.1643)	-0.02473 (0.01297)*	-0.02596 (0.01855)	-0.00658 (0.00589)
Δ LPLATt-2	0.02153 (0.02196)*	0.01311 (0.01096)	-0.02093 (0.02006)	-0.05449 (0.01583)***	-0.02663 (0.02265)	-0.00584 (0.00719)
Δ LPALLt-2	0.00957 (0.0145)	0.00212 (0.00723)	-0.01042 (0.01324)	0.02964 (0.01045)***	0.0376 (0.01495)**	0.00097 (0.00474)
Δ LERt-2	0.03077 (0.00024)	0.00886 (0.01979)	-0.2588 (0.03623)	-0.01904 (0.02859)	-0.03437 (0.0409)	-0.01022 (0.01298)

Note: Standard errors are in parenthesis. ***, **, * represent significance at 1%, 5% and 10% respectively. L denotes the log. Operator, Δ stands for the difference operator, WTI stands for oil, SILV for silver, PLAT for platinum, PALL for Palladium and ER for exchange rates

Panel C on the table indicates the short-run relationships of the variables and their lags. These coefficients can be interpreted as elasticities and indicate how fast each variable regains equilibrium after a short run shock. As earlier mentioned, oil prices are affected by several factors including geopolitical factors as such changes in these factors in the short run cause rapid swings in oil prices. Nevertheless, it is worth noting that changes in the nominal spot oil prices do not carry any significant information with reference to exchange rate behaviors. The results on panel C support this assertion as oil is highly significant at a 1% level in both its first and second lags. Changing oil prices are also seen to impact in the short run on silver prices. Oil has a close relationship with silver and is used as a production input and thus any significant changes in oil price will also affect silver prices in the short run.

Changing demand for jewelry, hoarding, amongst other factors significantly affect gold prices particularly in the short run. Of all the precious metals, changing gold prices affect silver the most mainly because they share investment and monetary features. Platinum price changes are generally influenced by changes in the prices of the other precious metals except for gold. There is significant impact of its prices with regards to oil and palladium most likely because of their high industrial uses. Changing exchange rates are significant in the first lag and also highly significant to changing gold prices in both the first and second lag. Gold is traded globally in US dollars hence in the long run; volatile exchange rates are more likely to account for changing gold prices in the long run. Moreover, gold is heavily retained by many central banks as part of their reserve portfolio which may be used to stabilize the economy during periods of high unexpected inflation (Aizenman and Inoue, 2012)

3.4 Conclusion and Policy Implications

This section on the thesis investigates the rapport between changing spot prices of oil, selected precious metals and the dollar/euro exchange rate. The cointegration test results indicate that there is a long run relationship between our variables in the system. The results of the VECM posit that compared to silver, gold prices take a much longer time span to regain equilibrium in the long run as expected. This finding is supported by previous research that concluded that gold is an asset that is highly resistant to inflationary shocks as previously mentioned. In addition, silver has enormous industrial uses and has been alleged to have lost its monetary to its industrial applications. Moreover, many studies suggest that gold is still the most preferable precious metal of choice to be included in most smart investors' portfolios. Gold is used as a hedge asset during periods of high commodity price volatility and a long run hedge against inflation. Platinum and palladium are prominently uses as close industrial substitutes in the automobile industry for making catalytic converters for engine exhausts. Regardless of their closes substitutability, palladium prices are seen to adjust to their long run equilibrium price than the price of platinum.

Unprecedented changes in the price of oil affect the other commodity prices since oil is a major input in the production of precious metals. Oil prices fluctuations in the short run are triggered by a multitude of factors including market forces, geographic, political factors as well as decisions from the OPEC countries. Nevertheless, it is worth noting that changes in the nominal spot oil prices do not carry any significant information with reference to exchange rate behaviors. Many stakeholders particularly traders and investors would benefit from these findings since this

information would guide the inclusion or exclusion of palladium at different times from an active portfolio. As palladium continuously plays catch up with its “rich cousin” platinum, it may become highly sought out because they are close industrial neighbors just as gold and silver are close investment and monetary assets.

Our findings may serve to guide consumers’ decisions regarding purchases of durable goods at different times made from these commodities. Investors and traders in oil and precious metals can reasonable use the information transmitted through their price fluxes to make conjectures regarding investment and hedging strategies. Decisions of oil importing/exporting countries may be guided if they particularly monitor oil price changes. These findings shed more light in response to the question posed in the introductory section of this thesis regarding the most informative commodity in the group, and whether there exist a long run relationship between these commodity prices.

Chapter 4

PRECIOUS METAL PRICE DYNAMICS IN A REGIME CHANGING ENVIRONMENT: A MARKOV- SWITCHING APPROACH

4.1 Introduction

As mentioned in the introductory section, some researchers emphasize that the co-movements of commodity prices carry more reliable information to market participants than consumer prices (Mahdavi and Zhou, 1997). The information contained in commodity futures prices also provides a channel for speculative trading in futures markets which is then reflected in their spot prices (Hu and Xiong, 2013). It would be thought-provoking to know if the co-movements in commodity prices differ and convey varying information or are consistent with each other within a given state of the economy. It will also be stimulating to know which of the selected commodity prices conducts the most valuable information in a regime-changing environment. Similarly, we pursue an answer to some inquiries such as: which of the commodities under consideration can be used as an effective hedge asset if their prices move in unison during normal and volatile states of the economy; and which commodities can be used as a safe haven? Many stakeholders have pondered these questions particularly when considering investing in these commodities.

In this section on the study of the transmission mechanism between the spot prices of crude oil and the four selected precious metals, and their interactions with the US dollar/euro exchange rate, we employ a more dynamic methodology than many other researchers. The frequent changes in the equilibrium relationship between these commodity prices render the parameter constancy assumption of the traditional vector error correction (VEC) models too restrictive and the model may be incorrectly specified. Given the chain of financial crisis in the preceding decades, the parameter constancy assumption cannot stand in face when there are spontaneous financial crises, demand shocks and supply interruptions and discoveries. Therefore, we apply the Markov-switching vector error correction (MS-VEC) model and develop regime-dependent impulse response functions (RDIRF) to determine how the impact of a shock in the price of one of the commodities or the exchange rate is transmitted to the other variables in the system in a regime changing environment.

Although some studies in the literature like those of Thompson et al., (2002), Goshray (2002), Barassi & Goshray (2007) use sophisticated techniques to analyze the world market price transmissions, they neither focus on the selected precious metals nor use the Bayesian MS-VEC. Instead, they concentrate on agricultural and other products unlike our focus on selected precious metal prices and oil prices. This is one aspect that sets this study apart from previous studies on commodity price transmission. Awokuse and Yang (2003)⁹ find that the Commodity Research Bureau (CRB)¹⁰ Index, which represents a group of commodities prices, carries substantial

⁹ Marquis and Cunningham (1990), Cody and Mills (1991) and Hua (1998), among others, share a controversial belief with Awokuse and Yang (2003).

¹⁰ The CRB computes this index by taking an arithmetic average of 19 commodities including our four strategic commodities. Nevertheless this index includes both related and unrelated commodities and may somehow be a misrepresentative since information transmissions may be neutralized between heterogeneous commodities.

information that can forecast the future path of interest rates, industrial productivity and inflation.

We seek to determine the most informative commodity in the group, and which one transmits the lowest impact on the others after a shock strikes, taking into account the prevailing regimes. We posit that the MS-VEC approach is more reliable to apprehend the nonlinear structure of variations in the prices in different regimes as opposed to the conventional threshold models (Ihle and von Cramon-Taubadel, 2008). We discriminate between the short-run and long-run dynamics, allow for nonlinearity and adequately specify the nonlinear dynamics between the variables of interest by identifying the potential latent regimes in the data. Investigating nonlinearity and structural changes has attracted special interest in the light of the 2007/2008 global financial crisis and the 2010-2012 euro-zone debt crisis.

To the best of our knowledge, previous research which used the MS-VEC technique focused on agricultural and/or industrial commodities and not precious metals (e.g. Djuric et al., 2012; Listorti and Esposti, 2012). This study however selected commodities that are highly important in a multiple of industrial activities, global financial markets and diversified portfolios. In contrast to studies that have dealt with commodity price transmission and used commodity indices prevailing in one regime (Pindyck and Rotemberg, 1990), this study focuses on related commodity prices in a two-state economy and examines regime-dependent impulse response functions.

The merits of this study over others are fivefold. First, our findings are more robust than those of other studies because the proposed model efficiently captures the nonlinear dynamics of the price changes in an uncertain economic environment. The

Bayesian MS-VEC model and the Bayesian regime dependent impulse response analysis, which is not used by any of the previous studies, allow for time-varying interactions among the variables and hence the methodology used in this thesis is a more robust approach for modeling structural changes or regime shifts in the markets. Second, our results are more reliable because we use more closely related commodities, thereby limiting the information dilution inherent in the studies that use unrelated commodities. Moreover, our data covers a fairly long period with several major events.

Third, unlike other studies that target a single state economy, we present a more realistic finding by considering a two-state economy which is more pragmatic. Fourth, we employ a more flexible form of the model that allows both the coefficients and variances to change based on the prevailing regime. Fifth, the paper uses the Bayesian estimation which is robust to model misspecification and allows for the estimation of the impulse response functions and their confidence intervals based on the Markov-chain Monte Carlo method (MCMC) of Gibbs sampling.

4.2 Literature Review

The persistent and time-varying co-movements of commodity prices with oil prices and exchange rates are of great interest to investors who contemplate making vital investment decisions in asset classes. As earlier mentioned, these price drivers are acute in undermining foreign exchange earnings especially in developing countries because commodities like gold and silver are often used as substitutes for the U.S. dollar particularly during recessions. Consequently, depreciation of the dollar as perceived in recent years has elicited a surge in the demand for these commodities¹¹,

¹¹ Gold and silver are usually considered “*safe haven*” commodities because their inherent values are supposedly unchanged during severe economic circumstances.

thereby driving their prices up. Given that these commodities are widely traded in US dollars, historical changes in the prices of commodities like gold, oil and copper have been known to adequately forecast the direction of the US economy (Coudert et al., 2007).

An overview of the literature on commodity prices can be categorized into price co-movements, information diffusion in the presence of economic fundamentals and nonlinearity in chaotic environments (Bhar and Hammoudeh, 2011). The pioneer works of Pindyck and Rotemberg (1990), Palaskas and Varangis (1991), Trivedi (1995) and Deb et al. (1996) were focused on heterogeneous commodities. Others like Cashin et al. (1999), Palaskas and Varangis (1991), Trivedi (1995) and Deb et al. (1996) Palaskas and Varangis (1991), Trivedi (1995) and Deb et al. (1996), amongst other disagree with the above researchers who asserted that unrelated commodity prices move together. As earlier mentions, Palaskas and Varangis (1991), Trivedi (1995) and Deb et al. (1996) used a multitude of time series methods in an effort to measure excess co-movement in commodity prices. As an alternative to using randomly selected commodities like the above mentioned researchers, our attention is on selected related commodities rather than a mix of both related and unrelated commodities. Consequently, in contrast to previous studies, our choice of variables circumvents the potential for information dilution inherent when heterogeneous commodities are studied.

Although Thompson et al., (2002) and Barassi & Goshray (2007) use complex procedures to explore the world market price transmissions, they did not focus on selected precious metals or use the Bayesian MS-VEC. Alternatively, they concentrate on agricultural and other products. Awokuse and Yang (2003) find that

the Commodity Research Bureau (CRB)¹² Index, which represents a group of commodities prices, carries substantial information that can forecast the future path of interest rates, industrial productivity and inflation. Marquis and Cunningham (1990), Cody and Mills (1991) and Hua (1998), among others, share a controversial belief with Awokuse and Yang (2003).

Soni (2013) investigate and further concludes the presence of nonlinearity in serial dependence for the Indian commodity market using the AR (p)-GARCH (1, 1) model. Barkoulas et al. (2012) examine whether crude oil spot prices are determined by stochastic or deterministic endogenous fluctuations, using both metric and topographic diagnostic tools. They conclude that stochastic rather than deterministic rules are present in the dynamics of the crude oil spot market. Not many studies have examined precious metal price volatility transmissions using a flexible form of the Bayesian MS-VEC model that allows both the coefficients and variances to change based on the prevailing regime, as we do in this study. To the best of our knowledge, Djuric et al. (2012) and Listorti and Esposti (2012) are some of the few studies that use the MS-VEC model to study commodity prices. Another study which uses two similar variables as we do is Beckmann and Czudaj (2013). Although those authors do not use all our selected commodities, they apply a non-Bayesian MS-VEC model to investigate the dynamic relationships between the oil price and the dollar exchange rate and find different causalities between them. Beckmann and Czudaj (2013) also employ the MS-VEC model that also allows for nonlinearity between the variables in different states and maintains an economically intuitive structural form.

¹² The CRB computes this index by taking an arithmetic average of 19 commodities including our four strategic commodities. Nevertheless this index includes both related and unrelated commodities and may somehow be a misrepresentative since information transmissions may be neutralized between heterogeneous commodities.

Compared to Beckmann and Czudaj (2013), our study allows for additional four precious metals prices to be included in the model and performs the Bayesian regime dependent impulse response analysis (RDIRF) based on the Gibbs sampling. Apart from Beckmann and Czudaj (2013), all of the other studies consider agricultural commodities in specific countries. On the other hand, we develop the Bayesian RDIRF that traces the magnitude and direction of the commodity prices' response resulting from an instantaneous shock in different states of the economy.

Our study also differs from others in that apart from focusing on unrelated and related commodities, or on agricultural goods in a single state like others, we add to the literature by studying the price transmission mechanism between related precious metals spot prices, oil and exchange rate. We therefore do not undermine the potential for information diffusion inherent when a cluster of heterogeneous commodities are used. In addition, a single state economy is unrealistic given that the states of the economy are dynamic rather than static. Given that the selected commodities are related and the economy is observed to be dynamic and the coefficients under each regime are time-varying, we therefore effectively capture the magnitude and impact of the price dynamics in different states of the economy, thereby presenting a more realistic picture. We use high frequency, broad and long data set which includes periods of great economic dynamism, hence enabling our series to provide more realistic and updated results.

4.3 Methodology

4.3.1. Markov-Switching Vector Error Correction (MS-VEC) Model

Initially pioneered by Sims (1980), the VAR models have proven to be very flexible and reliable in capturing the dynamic interactions among multivariate time series.

These models have been essentially expedient in unfolding the dynamic performance of economic and financial time series as well as being an excellent tool for forecasting. The model choice is steered by the fact that VAR models frequently provide superior predictions relative to univariate time series models and sumptuous theory-based simultaneous equations.

Over the last few decades, the existence of structural change or a regime shift in data has been a major challenge in macro econometric time series models (see Granger, 1996). Undeniably, the review papers by Hansen (2001) and Perron (2006) affirm that econometric applications should distinctly consider regime shifts. The popularly used VAR models also face complications arising due to structural breaks or regime shifts.

Recently, econometricians have presented new models that can adequately deal with certain types of structural changes. One of such attractive techniques that can manage structural breaks is the Markov switching (MS) method proposed by Hamilton (1990) and later extended to multivariate time series models by Krolzig (1997, 1999). The initial work by Hamilton (1990) examines univariate Markov-switching autoregression (MS-AR). Later on, Krolzig (1997, 1999) introduced the Markov-switching vector error correction (MS-VEC) which harnessed multivariate cointegrated VAR models. MS models fall within the category of nonlinear time series models as they are generated by nonlinear dynamic properties such as high moment structures, time-varying, asymmetric cycles, and jumps or breaks in a time series (Fan and Yao, 2003). The long time span of our data includes several influential events such as the 1990/1991 Gulf War, the 1997 Asian Crises, the 2003 Iraq War, and the 2007/2009 global recession. The data also cover a number of influential

financial crises. The MS models are rendered to fit well such time series data with crisis-recovery features and regime shifts.

Many studies including Hamilton (1989), Diebold, et al., (1994), Durland & McCurdy (1994), Filardo (1994), Ghysels (1994), Kim & Yoo (1995), and Filardo & Gordon (1998) have effectively utilized MS models to analyze macroeconomic time series. Numerous studies also have utilized the MS models in the context of stock market returns (e.g. Tyssedal & Tjostheim, 1988; Schwert, 1989; Pagan & Schwert, 1990; Kim, et al., 1998; Kim & Nelson, 1998). Following these studies, we thus consider the MS-VEC model, which with its rich structure accommodates the features of the precious metals prices, oil price, and exchange rate data we examine. The model choice unlike other traditional models not only efficiently captures the dynamics of the process in a co-integration space, but also has a more appealing structural form and provides economically intuitive results.

We adopt a methodology based on a vector-error correction (VEC) model with time-varying parameters where, given our objectives, the parameter time-variation directly reflects regime switching. In this approach, changes in the regimes are treated as random events governed by an exogenous Markov process, leading to the MS-VEC model. The state of the market at any point in time is determined by a latent Markov process, with the probability of the latent state process taking a certain value based on the sample information. In this model, inferences about the regimes can be made on the basis of the estimated probability, which is the probability of each observation in the sample coming from a particular regime.

The MS-VEC model we use to analyze the time-varying dynamic relationship between the precious metals prices, the crude oil price and the exchange rate is an extension of the class of autoregressive models studied in Hamilton (1990) and Krishnamurthy and Rydén (1998). It also allows for asymmetric (regime dependent) inference for the impulse response analysis. The structure of the MS-VEC model is based on the model studied in Krolzig (1997, 1999). Examples of these models, among others, include Psaradakis et al. (2004), Krolzig et al. (2002), and Francis and Owyang (2003). Our estimation approach is based on the Bayesian Markov-chain Monte Carlo (MCMC) integration method of the Gibbs sampling, which allows one to obtain the confidence intervals for the impulse response function of the MS-VEC model.

To be concrete, let R_t , F_t , G_t , L_t , P_t and A_t denote the spot US dollar/euro exchange rate, the spot crude oil price, the spot price of gold, the spot price of silver, the spot price of platinum, and the spot price of palladium,¹³ respectively. Define the time-series vector X_t up to and including period t as $X_t = [R_t, F_t, G_t, L_t, P_t, A_t]'$ and let $\hat{A}_t = \{X_t | t = t, t-1, \dots, 1 - p\}$, where p is a nonnegative integer. For the vector-valued time series X_t of random variables, assume that a density (probability) function $f(X_t | \hat{A}_{t-1}, q)$ exists for each $t \in \{1, 2, \dots, T\}$. The parameters and the parameter space are denoted by θ and Θ , respectively. The true value of θ is denoted by $\theta_0 \in \Theta$. Let the stochastic variable $\mathcal{S} \in \{1, 2, \dots, q\}$ follow a Markov process (chain) with q states. In the MS-VEC model, the latent state variable \mathcal{S} determines the probability of a given state in the economy at any point in time. Taking into

¹³ All of the six time series we analyze are nonstationary time series as shown by the unit root tests given in Table 4. However, these series maintain a cointegration relationship (Table 5), leading to the MS-VEC model.

account that the precious metal prices, exchange rate, and the oil price are cointegrated but their dynamic interactions are likely to have time-varying parameters,¹⁴ our analysis is based on the following MS-VEC model:¹⁵

$$DX_t = m_{\mathcal{S}_t} + \sum_{k=1}^{p-1} G_{\mathcal{S}_t}^{(k)} DX_{t-k} + P_{\mathcal{S}_t} X_{t-1} + e_t, \quad t = 1, 2, \dots, T \quad (4)$$

where p is the order of the MS-VAR model, $e_t | \mathcal{S}_t \sim N(0, W_{\mathcal{S}_t})$ and $W_{\mathcal{S}_t}$ is a (6×6) positive definite covariance matrix. The random state or regime variable \mathcal{S}_t , conditional on \mathcal{S}_{t-1} , is unobserved, independent of past X_s , and assumed to follow a q -state Markov process. In other words, $\Pr[\mathcal{S}_t = j | \mathcal{S}_{t-1} = i, \mathcal{S}_{t-2} = k_2, \dots, \hat{A}_{t-1}] = \Pr[\mathcal{S}_t = j | \mathcal{S}_{t-1} = i, \hat{A}_{t-1}] = p_{ij}$ for all t and k_l , regimes $i, j = 1, 2, q$, and $l \geq 2$. More precisely \mathcal{S}_t follows a q -state Markov process with a transition probability matrix given by:

$$P = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1q} \\ \vdots & \vdots & & \vdots \\ p_{q1} & p_{q2} & \dots & p_{qq} \end{bmatrix}, \quad \sum_{j=1}^q p_{ij} = 1. \quad (5)$$

As such, p_{ij} is the probability of being in regime j at time t , given that the economy was in regime i at time $(t-1)$, where i and j take possible values in $\{1, 2, \dots, q\}$. The MS-VEC model specified as above allows all parameters to depend on the latent

¹⁴ Several studies find that the dynamic links between the oil and stock prices are sensitive to the sample period. Ciner (2001) finds strong linkages between oil prices and the stock market in the 1990s, but not in the 1970s and 1980s. Silvapulle and Moosa (1999) using daily data covering the period 1985–1996 report that their findings support the oil futures prices leading the spot prices but more importantly there may be a changing pattern of leads and lags over the time period under considered.

¹⁵ Camacho (2005) shows that the asymmetric dynamics of the equilibrium errors lead to the MS-VEC model.

regime or state variable S_t , that is, all parameters of the model including the variance matrix W_ς are time-varying.

The long-run relationships between the six variables in the MS-VEC model specified in Equation (4) are contained in the P_ς matrix. We can interpret switching P_ς in three ways: switching in the co-integrating vectors, the weighting matrix, or both. Although, these approaches are de facto equivalent, our specification in the error-correction term implies a single set of long-run relationships and preserves the Engle-Granger notion of co-integration. The long-run impact matrix P_ς is written as:

$$P_\varsigma = a_\varsigma b\iota. \quad (6)$$

Here, P_ς stand for the state-dependent, long-run impact matrices defined by the $(r \times n)$ matrix of the co-integrating vectors β and the $(n \times r)$ state-dependent¹⁶ weighting matrix a_ς .¹⁷ While β represents the coefficients of the long-run impact which is assumed to be unchanged over the entire sample period, and hence regime-independent, a_ς stands for the regime-dependent adjustment coefficient that controls how the endogenous variables respond to the disequilibria represented by the r -dimensional vector $b\iota X_{t-1}$. As such, a key distinction of the MS-VEC model in Equations (4)-(6) is that the speed at which the variables adjust to the long-run equilibrium varies across regimes. For example, a shock in the oil price will have a

¹⁶ Following Krolzig (1997, 1999), we estimate the parameters in the cointegration vector β using the Johansen (1988, 1991) method by imposing one cointegration relationship since the tests support the existence of only one cointegration relationship. These estimates enter the MS-VEC model as predetermined.

¹⁷ Our specification assumes constant and regime-independent cointegration vectors, while allows for the presence of the regime-dependent adjustment to the equilibrium. This specification is consistent with the nonlinear adjustment to the equilibrium examined in Savit (1988).

different impact on the exchange rate and the four metal prices, depending on whether the economy is in a low or high volatility regime. In this model, due to the nonlinear dynamics of the equilibrium errors,¹⁸ denoted by $z_t = b\epsilon X_t$, both the strength with which the equilibrium errors are corrected (measured by the matrix a_ς) and the short-run dynamics of the endogenous variables (measured by the matrices G_ς) are time-varying. In our specification, the switches can be interpreted as alterations across regimes in the rate at which the long-run relationship is attained.

In our particular application, the maintained hypothesis is that $q=2$, that is, two states or regimes for each variable are sufficient to describe the dynamic interactions among the variables we scrutinize. This is consistent with crisis-recovery (recession-expansion) cycles observed in many financial and macroeconomic time series. A large number of studies show that the two-regime MS model is rich enough to capture the regime-switching behavior in financial and macroeconomic time series (e.g., Hamilton, 1989; Diebold, et al., 1994; Durland & McCurdy, 1994; Filardo, 1994; Ghysels, 1994; Kim & Yoo, 1995; and Filardo & Gordon, 1998).

The MS-VEC model in Equations (5)-(7) has quite significant appealing properties for analyzing the dynamic interactions of the variables in the short-run and also in terms of their responses to disequilibria. First, it allows one to classify regimes as depending on the parameter switches in the full sample, therefore, breeding the potential to detect the changes in dynamic interactions among the variables. Second, this model allows for many possible changes in the dynamic interactions among the

¹⁸ Although the long-run parameters (represented by matrix β) are state-independent, Camacho (2005) shows that the equilibrium errors follow an MS-VAR model under the specifications in Equations (5) and (7). Indeed, Equation (5) can be obtained from a model where the equilibrium errors follow an MS-VAR process.

variables at unidentified periods. Third, it is possible to make probabilistic inference about the dates at which a change in regime occurred. We will be able to evaluate the extent of whether a change in the regime has actually occurred, and also identify the dates of the regime changes. Finally, this model also allows one to derive the regime-dependent impulse response functions to summarize whether the impact of a shock in one variable on other variables varies across the regimes.

In order to estimate the appropriate MS-VEC model, the empirical procedure commences with identifying a set of conceivable models. We use the Bayesian Information Criterion (BIC) in a linear VAR (p) model to determine the order p of the MS-VEC model. The MS-VEC model provisions may differ in terms of the regime numbers (q) and the variance matrix specification. We only consider regime-dependent (heteroscedastic) variance models, because all six time series we analyze span a number of periods where volatilities vary significantly (see Table 1). Once a specific MS-VEC model is identified, we next test for the presence of nonlinearities in the data. In testing the MS-VEC model against the linear VEC alternative, we follow Ang and Bekaert (2002) and use the likelihood-ratio statistic (LR), which is approximately $\chi^2(q)$ distributed, where q is equal to the number of restrictions plus the nuisance parameters (i.e., free transition probabilities) that are not identified under the null. We use the p -values based on the conventional χ^2 distribution with q degrees of freedom and also for the approximate upper bound for the significance level of the LR statistic as derived by Davies (1987). Once we establish nonlinearity,

we can choose the number of regimes and the type of the MS model based on both the likelihood-ratio statistic and the Akaike information Criterion (AIC).¹⁹

A two-step procedure is implemented to estimate the MS-VEC model owing to that used by Krolzig (1997), Saikkonen (1992), Saikkonen and Luukkonen (1997), Krolzig, et al. (2002), and Saikkonen and Lütkepohl (2000). All the estimators for our model are asymptotically normally distributed and the usual statistical inference applies given that all variables in the MS-VEC model are stationary, (Krolzig, 1997; Saikkonen, 1992; Saikkonen & Luukkonen, 1997; Krolzig, et al., 2002). To begin with, the Johansen (1988, 1991) procedure is used to ascertain the number of co-integrating relationships. The equilibrium errors $z_t = b'X_t$ are obtained in this first step. Thereafter, the z_t determined in the first step is used to estimate the MS-VEC model. Saikkonen (1992) and Saikkonen and Luukkonen (1997) show that the Johansen procedure estimates the co-integrating vectors consistently even in the presence of regime switching.

Of the three universally applied techniques for estimating the parameters of the MS models, the simplest method of estimation is the maximum likelihood (ML). Nonetheless, it may be computationally demanding and may have slow convergence.²⁰ The ML method faces two important practical difficulties. First, global maximum of the likelihood may be difficult to locate. Second, the likelihood function for the important class of mixtures of normal distributions is not bounded

¹⁹ Krolzig (1997) and Psaradakis and Spagnolo (2003) suggest selecting the number of regimes and the MS model using the AIC. Using Monte Carlo experiment, Psaradakis and Spagnolo (2003) show that the AIC generally yields better results in selecting the correct model.

²⁰ An excellent review of the ML estimation of the MS models is provided by Redner and Walker (1984).

and the ML estimator does not exist for the global maximum. The more commonly used method of estimation for the MS models is the expectation maximization (EM) algorithm (Dempster et al., 1977; Lindgren, 1978; Hamilton, 1990, 1994). Assuming that the conditional distribution of X_t given $\{\hat{A}_t, \mathbf{S}_t, \mathbf{S}_{t-1}, \dots, \mathbf{S}_0; \varrho^c\}$ is normal, the likelihood function is numerically approximated using the EM algorithm in two steps. The initial step takes into account that, given the current parameter estimates and the data, the conditional expectation of the log likelihood is computed (E-step), and in the second step the parameters that maximize the complete-data log likelihood function are computed (M-step). The EM algorithm may have slow convergence and also the standard errors of the parameters cannot be directly obtained from the EM algorithm. A third option is the Bayesian MCMC parameter estimation based on the Gibbs sampling. The ML and EM methods usually fail for certain types of models since it may not be possible to compute the full vector of likelihoods for each regime for each period. The MCMC works only with one sample path for the regimes rather than a weighted average of sample paths over all regimes, and therefore, avoids the problem faced by the ML and EM methods.

The MCMC indeed treats the regimes as a distinct set of parameters. Our MCMC implementation is based on the following steps:²¹

- Draw the model parameters given the regimes. In our case, transition probabilities do not enter this step.
- Draw the regimes given the transition probabilities and the model parameters.
- Draw the transition probabilities given the regimes. In our case, the model parameters do not enter this step.

²¹ See Fruehwirth-Schnatter (2006) for details on the MCMC estimation of the MS models.

The first step involves drawing the variance matrix W_{ς} given the regimes, the transition probabilities P and the parameters $h_{\varsigma} = (b, m_{\varsigma}, a_{\varsigma}, G_{\varsigma})$ using a hierarchical prior. Our implementation first draws a common covariance matrix from Wishart distribution given the inverse of the regime specific covariance; and second we draw the regime specific covariance from the inverse Wishart distribution given the common covariance. The degrees of freedom priors for the Wishart and the inverse Wishart distributions are both equal to 4. Second, we use a flat prior and draw $h_{\varsigma} = (b, m_{\varsigma}, a_{\varsigma}, G_{\varsigma})$ given the regimes, the transition probabilities P , and the variance matrix W_{ς} from a multivariate normal distribution with a 0 mean. In the second step, we draw the regimes S_t , given $h_{\varsigma} = (b, m_{\varsigma}, a_{\varsigma}, G_{\varsigma})$, the transition probabilities P , and the variance matrix W_{ς} . This is obtained from Bayes' formula, where relative probability of regime i at time t is given as the product of the unconditional regime probability times the likelihood of regime i at time t . Regimes are drawn as a random index from $\{1 \dots q\}$ given the relative probability weights. Indeed, we use the Forward Filter-Backwards Sampling (FFBS) (also called Multi Move Sampling) algorithm described in Chib (1996) to draw the regimes. In the second step of the MCMC method, we reject any draws if less than 5% of the observations fall in any of the regimes. Finally, in the third step the unconditional probabilities P given the regimes are drawn from a Dirichlet distribution. We set the priors for the Dirichlet distribution as an 80% probability of staying in the same regime and a 20% probability of switching to the other regime. We perform the MCMC integration with 50,000 posterior draws with a 20,000 burn-in draws.

4.3.2 Regime-Dependent Impulse Response Functions

The pioneer work of Sims (1980) was the first to introduce regime-dependent the impulse response function (RDIRF's). Since then, it has been considered a natural tool to analyze the dynamic interaction between the metal prices, the crude oil price, and the exchange rate. IRF analysis examines how a given magnitude of a shock in one variable propagates to all variables in the system over time, say for $h=1, 2, \dots, H$ steps after the shock hits the system. Computing the multi-step IRFs from the MS-VEC models as well as from all nonlinear time series models proves complicated because no ordinary method of computing the future path of the regime process exists. An ideal IRF analysis requires that we know the future path of the regime process, since the impulses depend on the regime of the system in every time period.

In a perfect case, the IRFs of the MS-VEC model should integrate the regime history into the propagation period, which is not easily resolved. Two approaches arose in the literature as a solution to the history dependence problem of the IRFs in the MS-VEC models. Ehrmann et al. (2003) suggest assuming that the regimes do not switch beyond the shock horizon, leading to regime-dependent IRFs (RDIRF). On the other hand, Krolzig (2006) acknowledges the history dependence and allows the regime process to influence the propagation of the shocks for the period of interest, $h=1, 2, \dots, H$. In Krolzig's approach conditional probabilities for future regimes, \mathcal{S}_{t+h} are obtained given the regime \mathcal{S}_t and the transition probabilities, P .

One outstanding attraction of the RDIRF analysis is the possibility of determining the time variation in the responses of variables to a particular shock. The RDIRF traces the expected path of the endogenous variables at time $t+h$ after a shock of a

given size to the k -th initial disturbance at time t , conditioned on regime i . The k -dimensional response vectors $\psi_{ki, 1} \dots \psi_{ki, h}$ represent a prediction of the responses of the endogenous variables (Ehrmann et al. 2003). The RDIRFs²² can be defined as follows:

$$y_{ki,h} = \frac{\mathbb{1}E_t X_{t+h}}{\mathbb{1}u_{k,t}} \Bigg|_{S_t = \dots = S_{t+h} = i} \quad \text{for } h \geq 0 \quad (7)$$

where $u_{k,t}$ is the structural shock to the k -th variable. Generally, the reduced form shocks e_t will be correlated across the equations and $e_{k,t}$ will not correspond to $u_{k,t}$. This results to the well-known identification problem for which several solutions exist. We assume that the structural shocks are identified as $e_t = F_{\mathfrak{S}} u_t$, where $F_{\mathfrak{S}}$ is a (6×6) matrix relating the reduced form shocks to the structural shocks. To make structural inferences from the data, the structural disturbances and hence F must be identified. In other words, sufficient restrictions are imposed on the parameter estimates in order to derive a separate structural form for each regime, from which RDIRFs are then computed. As in a standard VAR measuring, we order the variables in this way: the exchange rate, the crude oil price, the price of gold, the price of silver, the price of platinum, and the price of palladium. We use the recursive identification scheme, made popular by Sims (1980). The recursive identification scheme is based on the Cholesky decomposition of the covariance matrix as $W_{\mathfrak{S}} = L_{\mathfrak{S}} L'_{\mathfrak{S}}$ and the identifying structural shocks from $u_t = F_{\mathfrak{S}}^{-1} e_t$ with $F_{\mathfrak{S}} = L_{\mathfrak{S}}$.

The RDIRF analysis, although significantly simplifies the derivation and allows for the construction of confidence intervals via bootstrap, is not appropriate if the regime

²² Refer to Ehrmann et al. (2003) for details on characteristics and computation of the regime-dependent impulse responses.

switching is likely during propagations of shocks. The solution of Krolzig (2006) is appealing, but it leaves out the construction of the confidence intervals. In our study, we combine the RDIRF analysis with the MCMC integration. Given our interest is in determining whether the dynamic response of one variable to a shock in another variable depends on the state of the economy, the assumption of staying in a given regime would not allow for having the analysis we intend and also is not consistent with the regime-switching behavior of the economy. This is not consistent with the market's actual behavior because assuming a given fixed regime does not allow switching between states such as recovery or crash during the shock propagation periods. Building on the Bayesian impulse responses for the linear VAR models, which is well covered in Ni et al. (2007), we derive the posterior density of the RDIRFs from the Gibbs sampling. The simulations of the posteriors of the parameters jointly with the identification of the structural shocks via the Gibbs sampler directly yield the posterior densities of the RDIRFs. The confidence bands are obtained by the MCMC integration with a Gibbs sampling of 50,000 posterior draws with a burn-in of 20,000.

4.4 Results and Discussion

As mentioned before, the descriptive statistics are presented on Table 1 while the correlation matrices are presented in Tables 2 and 3. Also, the unit root and cointegration tests reveal that our variables are $I(1)$ and that there exists a long-run relationship between the variables. After establishing the existence of a long-run equilibrium relationship, the question is whether to use the ordinary VEC or the MS-VEC model. To answer this question, we first estimate the MS-VEC model with two regimes as described in Section 3. In order to make a choice between the VEC and MS-VEC models; we first perform the likelihood ratio (LR) test. The LR test against the

MS-VEC model is nonstandard due to the nuisance parameters. Therefore, we report the upper bound of the p -value of the LR test following the suggestion by Davies (1987). The results of the LR tests and the model selection criteria are reported in Table 5. The p -values of the ordinary, Chi-square approximations due to Ang and Bekaert (1998), and the Davies (1987) upper bound all reject the choice of the linear VEC, thus favoring the MS-VECM with two regimes (low and high volatility). Moreover, the Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the Hannan-Quinn information criterion all favor the MS-VEC model over the linear VEC model, which confirm the rejection of the linear VEC model.

After establishing that the data supports the MS-VEC model over the linear model, we estimate the two regime MS-VEC model using the Bayesian estimation method as earlier described. Some statistics about the properties of the estimated MS-VEC model are presented in Table 8. The transition probability of staying in low volatility regime (regime 1) is $\text{Prob}(S_t=1|S_{t-1}=1) = 0.856$ and the transition probability of staying in high volatility regime (regime 2) is $\text{Prob}(S_t=1|S_{t-1}=2) = 0.631$, which suggests that regime 1 has a higher probability than regime 2. Regime 1 is therefore implied to be the persistent state and this persistent property is also reflected in the durations of the regimes. The average duration of the low volatility regime is estimated as 6.960 days, while the average duration of the high volatility regime is estimated as 2.710 days. Furthermore, the computed transition probabilities $\text{Prob}(S_t=1|S_{t-1}=2) = 0.144$ and $\text{Prob}(S_t=2|S_{t-1}=1) = 0.370$ depict that the market is more than twice likely to switch from high volatility regime (regime 2).

Table 7: Estimation Results for the MS-VEC Model

<i>Model selection criteria</i>			
	MS(2)-VEC	Linear VEC(2)	
Log likelihood	122534.760	118130.404	
AIC criterion	-37.309	-35.996	
HQ criterion	-37.237	-35.961	
BIC criterion	-37.102	-35.894	
<i>LR linearity test</i>			
	Statistic	<i>p</i> -value	
	8808.712	$\chi^2(100)=[0.0000]$ ***	
		$\chi^2(101)=[0.0000]$ ***	
		Davies=[0.0000]***	
<i>Transition probability matrix</i>			
	$P = \begin{bmatrix} 0.856 & 0.144 \\ 0.370 & 0.631 \end{bmatrix}$		
<i>Regime properties</i>			
	Probability	Observations	Duration (months)
Regime 1	0.720	4718	6.960
Regime 2	0.280	1840	2.710

Note: The table reports estimation results and model selection criteria for the MS-VEC model given in Equations (5)-(7). The lag order is selected by the BIC in a VAR in levels as 2 for both linear VEC and MS-VEC models. The MS-VEC model is estimated using Bayesian Monte Carlo Markov Chain (MCMC) method where we utilize Gibbs sampling. The MCMC estimates are based on 20,000 burn-in and 50,000 posterior draws. All reported estimates in the Table for the MS-VEC model are obtained from the Bayesian estimation. The likelihood ratio statistic tests the linear VEC model under the null against the alternative MS-VEC model. The test statistic is computed as the likelihood ratio (LR) test. The LR test is nonstandard since there are unidentified parameters under the null. The χ^2 *p*-values (in square brackets) with degrees of freedom equal to the number of restrictions as well as the number of restrictions plus the numbers of parameters unidentified under the null are given. Regime properties include ergodic probability of a regime (long-run average probabilities of the Markov process), observations falling in a regime based on regime probabilities, and average duration of a regime. The *p*-value of the Davies (1987) test is also given in square brackets. The models are estimated over the full sample period 5/1/1987-17/2/2012 with 6558 observations. ***, ** and * represent significance at the 1%, 5%, and 10% levels, respectively.

Based on the ergodic (regime) probabilities, there are 4718 observations included in regime 1 comprising 72% of the entire sample size. The smoothed probability estimates of the MS-VEC model are given in Figure 2. The smoothed probability

estimates profoundly show that the periods that can be classified as high volatility regime (regime 2) always correspond to the crises periods. The economic crisis of 1997 may significantly explain the shift in the series between the two regimes, since the periods of high volatility regime are more frequently observed after 1997.

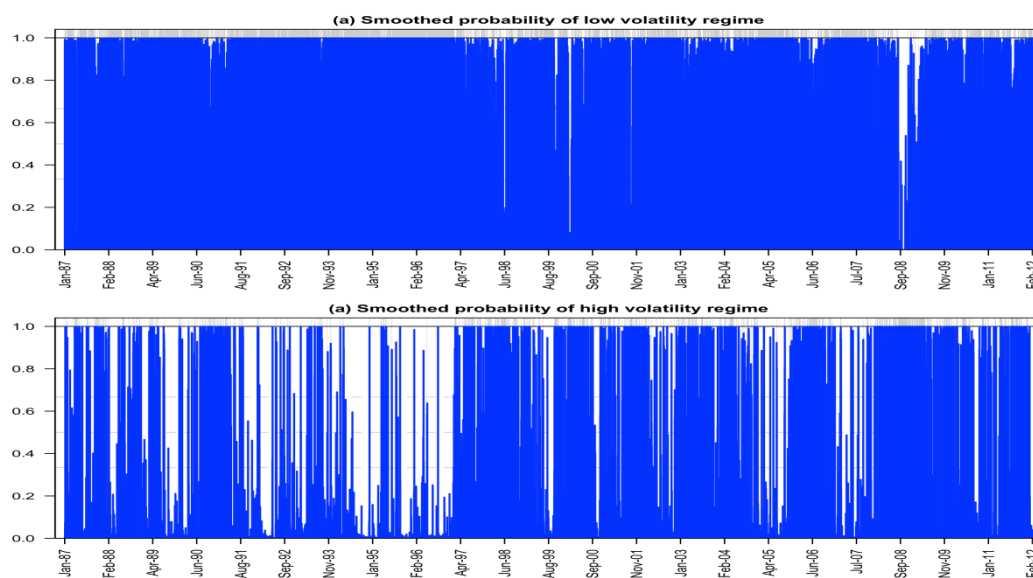


Figure 2: Estimate of Smoothed Probabilities

Note: The figures plot the smoothed probability estimates of (a) low volatility regime (Regime 1) and (b) high volatility regime (Regime 2). The smoothed probabilities correspond to the MS-VEC model in Equations (5)-(7). The lag order of the estimated MS model is 2 and selected by the BIC. The MS-VEC model is estimated using the Bayesian Monte Carlo Markov Chain (MCMC) method where we utilize the Gibbs sampling. The MCMC estimates are based on 20,000 burn-in and 50,000 posterior draws. The MCMC method uses the Forward Filter-Backwards Sampling (FFBS) algorithm (Multi-move sampling) described in Chib (1996) to sample the regimes. The smoothed probabilities in the figures are the means of the 50,000 posterior draws for each time period based on the FFBS algorithm. The shaded regions in the figures correspond to the periods where smoothed probability of the corresponding regime is the maximum.

The regime-dependent impulse response functions (RDIRFs) are used to analyze the magnitude and directional impact of unexpected innovations in the system. The RDIRFs and their confidence bands are estimated using the Gibbs sampling method explained earlier. Figures 3-8 trace the path of a one-standard deviation dynamic innovation resulting from a shock in the commodity prices. We choose 100 days as

the mean projected response period. The RDIRFs illustrate a more significant effect in regime 2 (high volatility regime) than in regime 1 (low volatility regime). In terms of the magnitude and the persistence, the impact of a shock is evidently different between the two regimes, thus justifying the relevance of the generation of RDIRFs to capture asymmetries in both states. On the whole, the initial impact of a one-standard deviation shock in the commodity spot prices is more significant in the second regime.

The impact of a shock caused by fluctuations in any of the variables in the system on the other commodity prices is different. In Figure 3, the fluctuating U.S. dollar/euro exchange rate significantly affects the price returns of all other commodities, especially when the system is in the high volatility regime (regime 2). The US dollar/euro exchange rate represents the price transmission variable in the system since all commodities are internationally traded in these two currencies. While in regime 1 the impact of an exchange rate shock is weak, the impact is stronger in regime 2 especially on oil prices. The co-integrated relationship between the oil price and the dollar exchange rate could explain why a shock in the exchange rate has the most impact on the oil price. This result is complementary to those of Sari et al. (2009).

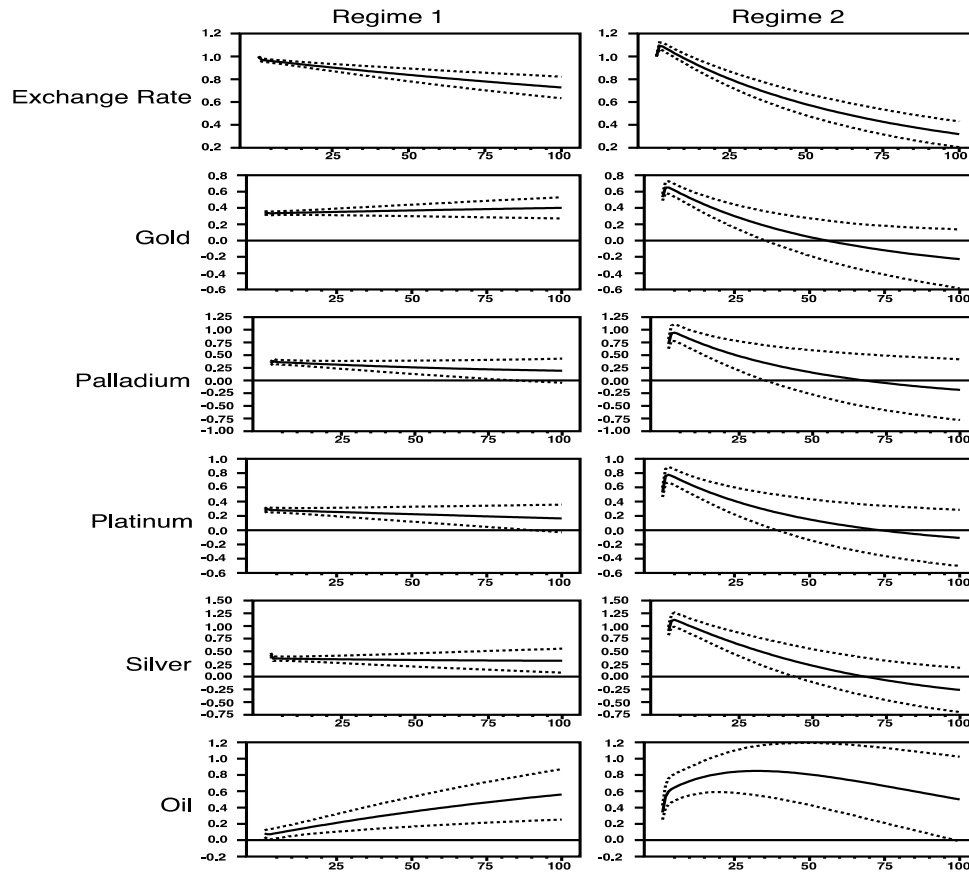


Figure 3: Regime-dependent Impulse Responses to an Exchange Rate Shock

Note: The figure gives the impulse response of the variable in the left row to a one 1 standard deviation shock in the US dollar/euro exchange rate. The horizontal axis represents the steps in days. The solid line is the impulse response and dotted lines are for 70% confidence interval. All impulses are based on Cholesky factor orthogonalization. The confidence intervals for the linear VEC model are obtained from 1,000 bootstrap resampling. The MS-VEC impulse responses are computed using the regime dependent impulse response method suggested by Ehrmann et al. (2003). The confidence intervals for the MS-VEC models are obtained from the 50,000 posterior draws for each step.

Figure 4 shows that the impacts of the oil price shocks in regime 2 are more significant than in regime 1 as expected. Coupled with oil's use as a major energy source traded in US dollars, changes in the oil price are caused specifically by economic events, geopolitical factors, wars, etc., thereby making the oil price volatility to have significant impacts on all other commodities (e.g. the 1999/2000 oil price shock, the 2008 financial meltdown etc.). The initial impact of an oil price

shock is positive on all other variables in regime 2, except for the exchange rate which gets initially depressed (appreciating the US dollar over the euro is about 0.02%) as a result of shock before it rises back. The response of the exchange rate to oil price shock is radically asymmetric depending on the regime of the market, the response rising from negative to positive in the high volatility regime while it is always negative in the low volatility regime.

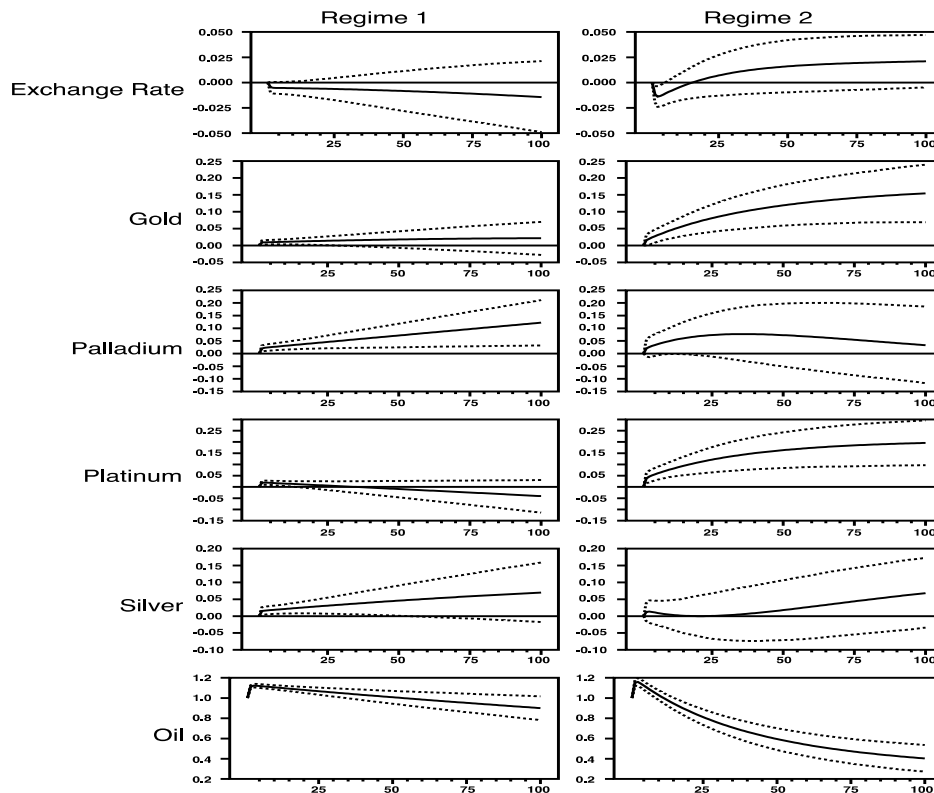


Figure 4: Regime-dependent Impulse Responses to an Oil Price Shock

Note: The figure gives the impulse response of the variable in the left row to a one 1 standard deviation shock in the oil price. The horizontal axis represents the steps in days. The solid line is the impulse response and dotted lines are for 70% confidence interval. All impulses are based on the Cholesky factor orthogonalization. The confidence intervals for the linear VEC model are obtained from 1,000 bootstrap resampling. The MS-VEC impulse responses are computed using the regime dependent impulse response method suggested by Ehrmann et al. (2003). The confidence intervals for the MS-VEC models are obtained from the 50,000 posterior draws for each step.

Despite gold being the least volatile commodity in the group, changes in its price however transmit the most significant effect on all other commodity prices as shown in Figure 5. In regime 1, the impact of fluctuating gold prices is a steady rise in all other commodity prices. Changes in gold prices may also breed a negative sentiment regarding the expected future inflation since gold is used as an inflationary hedge. During the highly volatile periods (regime 2), a gold price shock unlike the shocks in the other commodity prices (except the oil price shock which also appreciates the US dollar in the low volatility regime) initially depresses the dollar/euro (appreciating the US dollar) exchange rate which happens within the first five days before this exchange rate starts to gradually rise as can be seen in Figure 5.

The initial impact is the highest on the silver price returns (about 1.25%), while it is lowest on oil (0.50%), materializing within the first 5 days. This may be explained by the fact that gold and silver possess monetary values as well as investment features, and thus have the highest correlations. This result also consolidates the assertion that gold carries the highest information content in the group since its impact is most profound on the other variables especially in regime 2 before the impacts start to smoothen out. The positive impact of an initial gold price shock on the close industrial metals platinum and palladium mirror each other (about 0.8% each).

The impact of changes in the silver price on the other variables is seen in Figure 6. Unlike gold, the impact is rather less severe and also less conspicuous in both regimes. The effect of a silver price shock on oil prices in regime 2 decays to zero unlike its impact on the other commodities. Our finding is contradictory to Sari et al. (2009) who assert that the effect of changing prices of gold and silver mirrors each

other. The changes in silver prices affect the gold price returns by only about 0.07% in regime 2, while the impact of changes of the gold price on silver is about 1.25%.

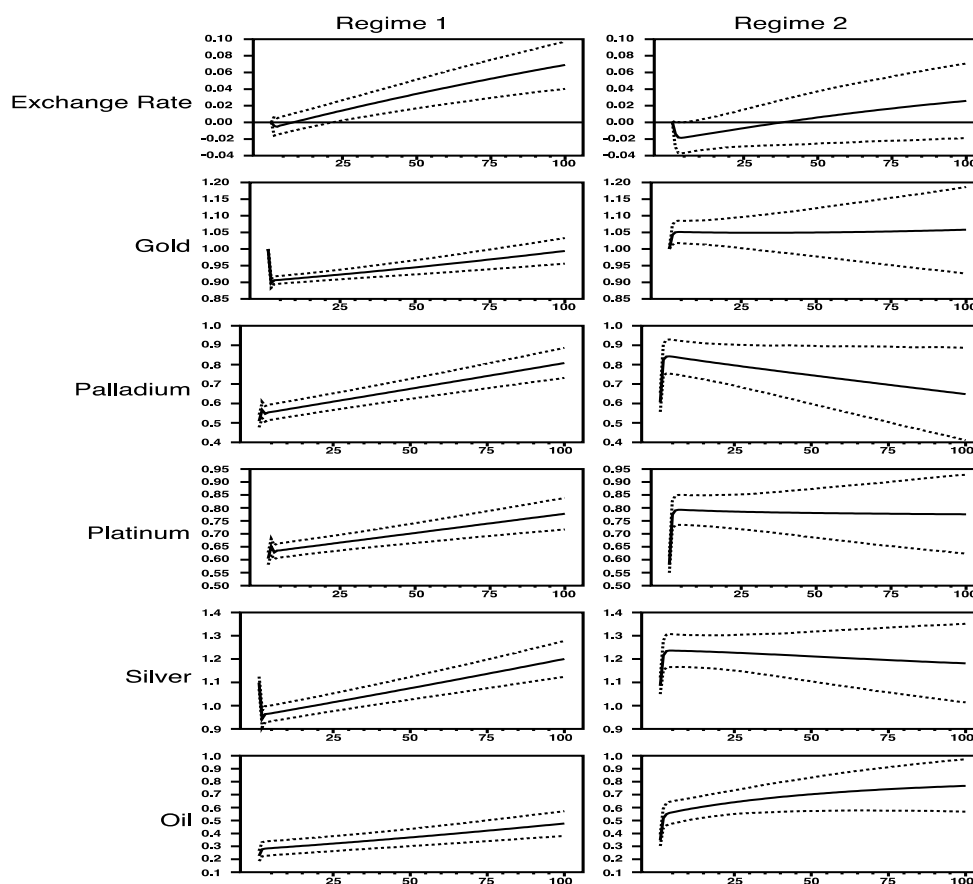


Figure 5: Regime-dependent Impulse Responses to a Gold Price Shock

Note: The figure gives the impulse response of the variable in the left row to a one 1 standard deviation shock in the gold price. The horizontal axis represents the steps in days. The solid line is the impulse response and dotted lines are for 70% confidence interval. All impulses are based on the Cholesky factor orthogonalization. The confidence intervals for the linear VEC model are obtained from 1,000 bootstrap resampling. The MS-VEC impulse responses are computed using the regime dependent impulse response method suggested by Ehrmann et al. (2003). The confidence intervals for the MS-VEC models are obtained from the 50,000 posterior draws for each step.

This shows that changes in the gold price affect the silver price return about 17 times more than the in the reverse scenario. The asymmetry in impulse responses to silver shocks not only consolidate the appropriateness of the MS-VEC model used, but also illustrates how misleading the analysis would be if based on linear models.

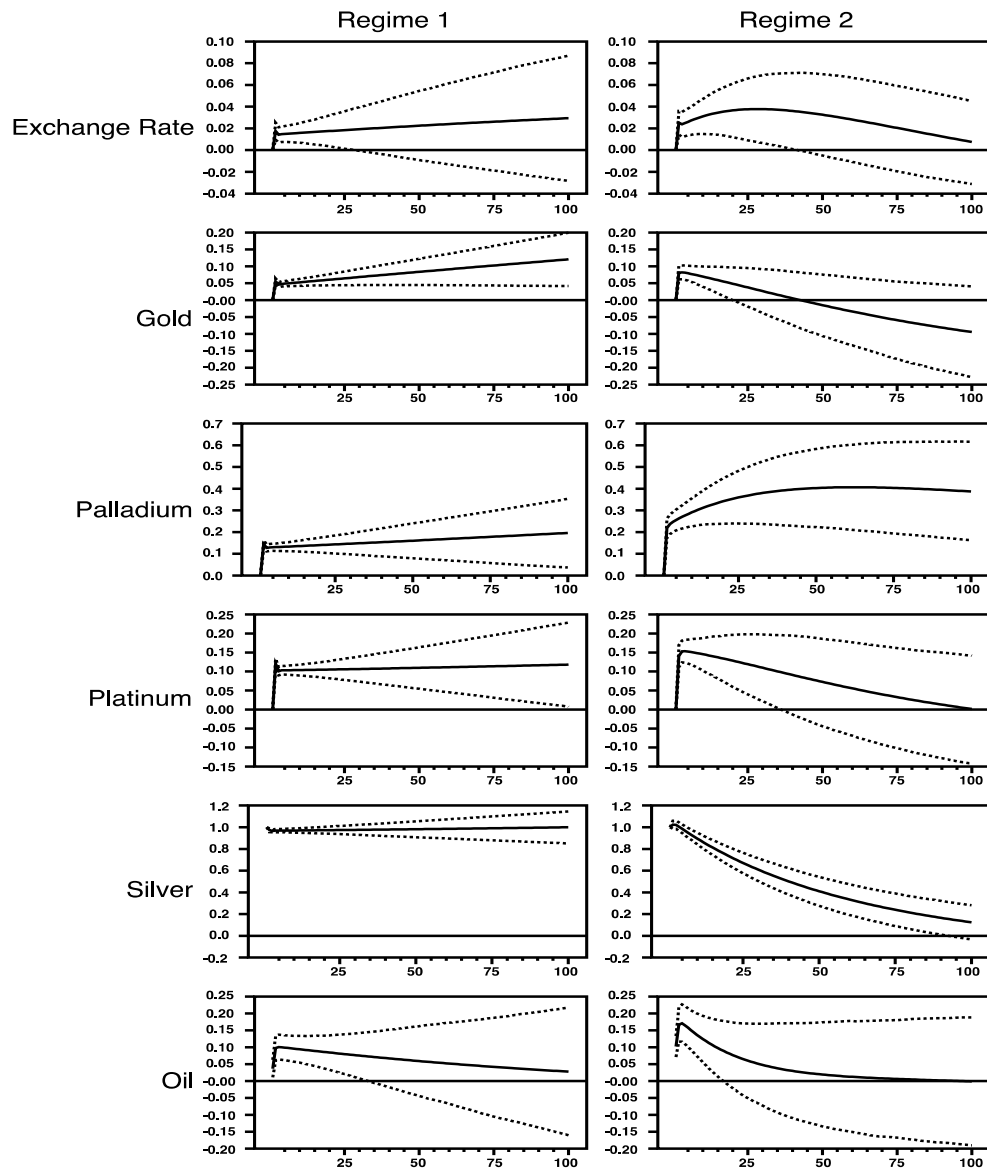


Figure 6: Regime-dependent Impulse Response to a Silver Price Shock

Note: The figure gives the impulse response of the variable in the left row to a one 1 standard deviation shock in the silver price. The horizontal axis represents the steps in days. The solid line is the impulse response and dotted lines are for 70% confidence interval. All impulses are based on the Cholesky factor orthogonalization. The confidence intervals for the linear VEC model are obtained from 1,000 bootstrap resampling. The MS-VEC impulse responses are computed using the regime dependent impulse response method suggested by Ehrmann et al. (2003). The confidence intervals for the MS-VEC models are obtained from the 50,000 posterior draws for each step.

As shown in Figure 7, although changes in the palladium price in regime 1 affect the exchange rate and oil prices significantly, the impact is rather weak on the other commodities. In regime 2, however, increases in the palladium price depress the dollar/euro exchange rate (appreciate the U.S. dollar) by about 2% in the first few days and the effect gets much significant over the horizon, thereby appreciating the US dollar significantly. The impact of a positive palladium price shock on the other commodities in regime 2 causes a fall in all price returns except for the oil return which rises. In addition to its low correlation with the other commodities, this makes palladium a good portfolio diversifier for investors in precious metals. Therefore, any form of price volatility compounded by its limited supply²³ triggers substantial jerks in the dollar/euro exchange rates as well as the prices of the other commodities.

As shown in Figure 8, changes in platinum prices impact the other commodity prices similarly to the impact of the changes in the palladium price on those commodities. This may be explained by the fact that both commodities derive their demand from the same industries. On the other hand, like in the case of palladium, a platinum price shock causes a rise in oil prices but depresses the palladium price returns, regardless of the state of the market.

²³ Russia and South Africa have about 80% of the world's palladium deposits. Concerns are usually raised when there is instability in the form of strikes in this sector because they will lead to strains in supply.

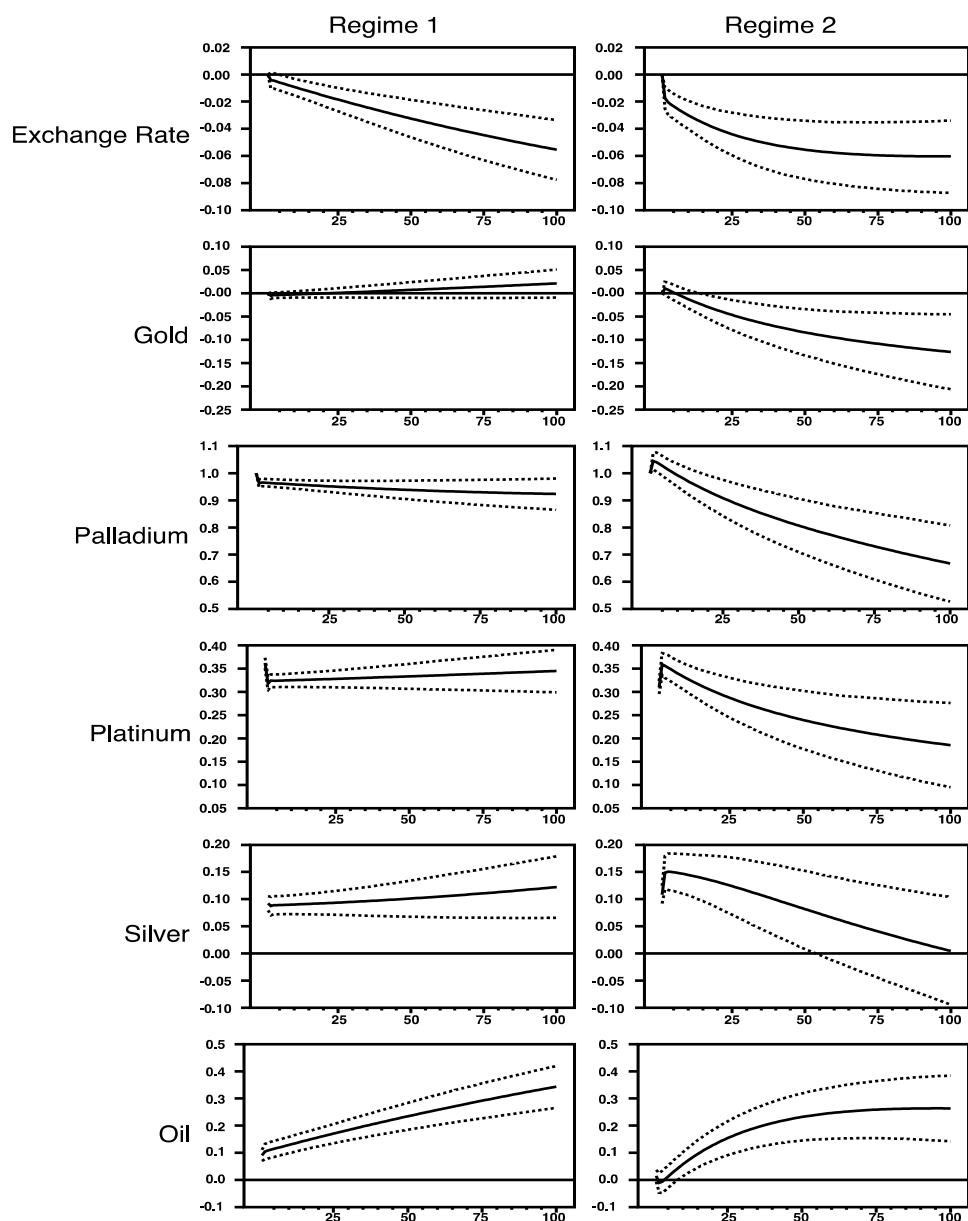


Figure 7: Regime-dependent Impulse Responses to a Palladium Price Shock

Note: The figure gives the impulse response of the variable in the left row to a one 1 standard deviation shock in the palladium price. The horizontal axis represents the steps in days. The solid line is the impulse response and dotted lines are for 70% confidence interval. All impulses are based on the Cholesky factor orthogonalization. The confidence intervals for the linear VEC model are obtained from 1,000 bootstrap resampling. The MS-VEC impulse responses are computed using the regime dependent impulse response method suggested by Ehrmann et al. (2003). The confidence intervals for the MS-VEC models are obtained from the 50,000 posterior draws for each step.

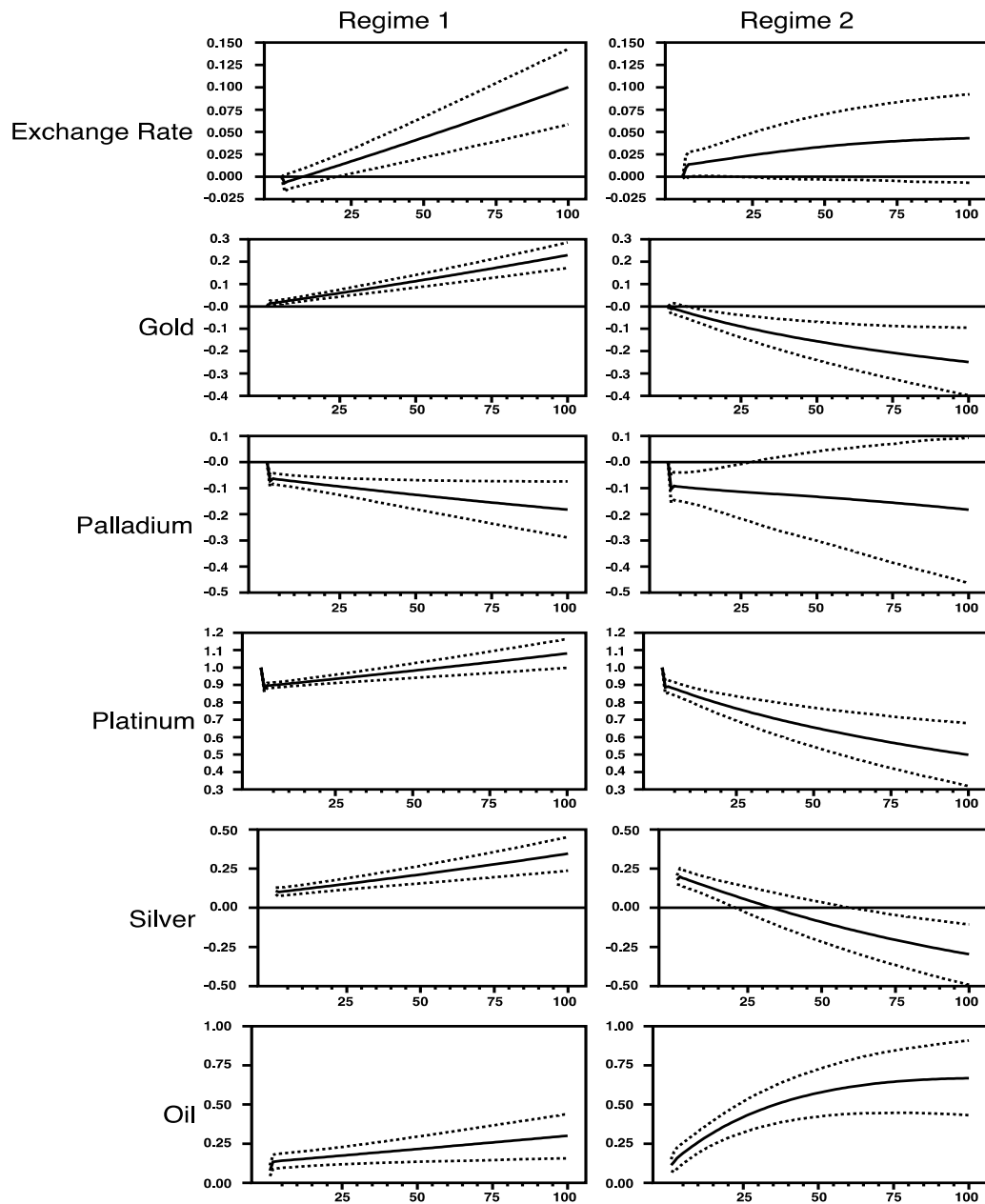


Figure 8: Regime-dependent Impulse Responses to a Platinum Price Shock

Note: The figure gives the impulse response of the variable in the left row to a one 1 standard deviation shock in the platinum price e . The horizontal axis represents the steps in days. The solid line is the impulse response and dotted lines are for 70% confidence interval. All impulses are based on the Cholesky factor orthogonalization. The confidence intervals for the linear VEC model are obtained from 1,000 bootstrap resampling. The MS-VEC impulse responses are computed using the regime dependent impulse response method suggested by Ehrmann et al. (2003). The confidence intervals for the MS-VEC models are obtained from the 50,000 posterior draws for each step.

4.5 Conclusion

This section views the information transmission dynamics between the spot prices of oil, gold, silver, platinum, palladium and the US dollar/euro exchange rate from a regime-switching perspective. This view is more realistic to a constantly changing market environment unlike an illusory single state economy. The MS-VECM used is economically intuitive and projects a somewhat realistic stance of a real economy. It accounts for both nonlinearities as well as the effect of instantaneous shocks of any of the variables in the system. Gold and platinum have the lowest historical volatility in the group. This presents gold as an inflationary hedge and platinum as an investment asset diversifier which recently moves in a lock-up with gold. The highest historical volatilities are from palladium and oil. Apart from its industrial use in making jewelry, silver is also widely used in the automobile industry like oil. Gold and silver have the highest historical correlation (95%), closely followed by oil and platinum (94%), thus suggesting the former pair as close monetary and investment assets, while the latter pair as close industrial neighbors. Gold has the lowest volatility amongst all variables in the group, which makes it an attractive hedge asset for diversifying investors' portfolios.

The MS-VEC model used for the analysis supports the presence of two regimes (low volatility and high volatility) with substantial information asymmetries. The initial and subsequent effect of increases in the gold price on the other variables is positive and significant in the both regimes, but the effect dampens in the high volatility regime. However, the gold impact on the US dollar/euro exchange rate is initially negative (i.e., dollar first appreciates) particularly in the high volatility regime but later becomes positive (i.e., depreciates and becomes less valuable) because the

fluctuations in its prices may transmit a negative sentiment regarding expected future inflation. Moreover, changes in the gold price have the most significant impact on silver prices, while the impact of those changes is the lowest for oil. This may be explained by the fact that gold and silver share similar features as monetary and investment assets, while gold and oil are mainly related in the long run because of their diverse uses.

Contrarily to the findings of some researchers²⁴ who assert that the effects of changing gold and silver price returns mirror each other, we find that changing gold prices affect silver price returns about 25 times more than silver prices affect gold price returns. Hence gold amongst the group of precious metals apparently has the highest information content in this group. Although we find that the effects of changes in gold price on platinum and palladium price returns to be similar, we notice significant asymmetries regarding the effects of fluctuations in both commodity prices on each other.

Coupled with its low historical correlation and volatility, palladium can be a good hedge for precious metal investors. Apparently, the platinum price increases affect palladium prices negatively, while the palladium price changes convey a positive effect on the platinum prices. This goes against the claim that the palladium prices play “*catch-up*” in their price returns with platinum. It is worth noting that, the effect of changes in the platinum price on the other commodities is minimal.

Increases in the palladium price which is expressed in U.S. dollar, however, depress exchange rate (appreciating US dollar and depreciating the euro) in both regimes and

²⁴ See Sari et al. (2009).

the gold price in regime 2. The most negative impact of the fluctuations in the palladium price falls on the exchange rate in both regimes. This may be due to a temporary loss of the hedging property of palladium. On the other hand, changes in the exchange rate affect all commodities significantly because they are all traded in US dollars. Changes in the exchange rate in the past since 2000 resulted from the weakening dollar, thus causing substantial spiking in commodity prices.

Based on our findings, we recommend that international investors consider including palladium in their precious metal portfolios since its low correlation makes it a good hedge asset. Investors of precious metal, central banks and other stakeholders should watch gold and oil prices carefully especially during high volatility regimes since they carry sufficient information that can determine the direction of change in the other commodity prices and exchange rate. Changes in the gold and oil prices can determine the direction of exchange rates hence central banks and governments can implement better policies to serve as a cushion especially during periods of high volatility. Investors and speculators should watch the changes in the gold price carefully as a change in direction may suggest whether to invest in silver or not. For the oil-importing and exporting countries, monitoring oil prices particularly in the high volatile regime is vital since it can act as a barometer to governments on how to implement effective policies to stabilize their exchange rates, inflation and balancing the budget.

Chapter 5

VOLATILITY IN PRECIOUS METAL IN THE PRESENCE OF OIL AND EXCHANGE RATE SHOCKS

5.1 Introduction

The last few decades have been swamped with dramatic financial crises that have compelled consumers, firms, investors and even entire countries to reconsider their investment strategies. As earlier mentioned, the 1997-1998 Asian crisis (AFC) resulted from short term capital flows that spread to other emerging equity and commodity markets. The 2001 U.S recession was triggered by the collapse of the dot-com boom which propelled a hike in bank liquidity. The most recent Global Financial crisis (GFC) saw the collapse of the real estate market in the U.S and spilled over through the financial system to the rest of the world. This crisis then extended and later unraveled to the 20010/2012 European debt crisis that led to bankruptcy of entire nations like Spain, Italy and Cyprus. These crises tend to cause excess volatility and contagion in financial markets. (Forbes and Rigobon, 2002; Lee et al., 2007; Markwat et al., 2009).

This recurrent contagious effect of failing financial markets tends to stir serious concerns to different stakeholders who ponder ways of safeguarding their investments through diversification. In a bid to protect themselves from possible unpredictable losses, amongst other investments, investors have recently turned to precious metals.

Precious metal prices have proven to move in synch since they are exposed to akin macroeconomic variables like interest rates, inflation and industrial productivity. Hammoudeh et al., (2007).

Over the years, research has focused on agricultural commodity prices e.g. corn, wheat, soya beans etc., and industrial commodities e.g. copper, iron steel etc. relative to precious metals. Of the selected precious metals, gold²⁵ and silver with their high monetary and investment features have attracted more attention in empirical research than their industrial counterparts (i.e. platinum and palladium). As a major energy source and its high price instability, oil prices react rapidly to distinct events like cold snaps, hurricanes, refinery outages and geopolitical event in oil producing countries. Hammoudeh et al. (2007) show that oil prices adjust to their long-run equilibrium prices faster than other commodities, thus inferring the importance of oil shock on our selected precious metals. In addition, shocks in the dollar and euro; the major currencies used for international global exchanges, can also impact these commodity prices. Coudert et al. (2008) find unidirectional causality from oil prices to the dollar exchange rate and that rising oil²⁶ prices cause appreciation of the dollar exchange rate. Therefore rising oil prices may lead to rising exchange rates, which in turn will affect the other commodities given that oil is a prime input in precious metal production, and the metals are also traded in US dollars.

Volatility forecasting is very popular in the literature and it is relevant for risk management, asset valuation and hedging strategies. There has been a great deal of

²⁵Gold is physically held in large quantities in central banks. Nevertheless they tend to under-report their international reserve to gold ratio position in order to minimize criticism when gold prices fall.

²⁶Aliyu and Rano (2009) find that real oil price shocks and exchange rate volatility impact positively on Nigeria's GDP

research on nonlinear models that exhibit or approximate long-memory. In some cases, the models incorporate some sort of regime switching between states. Granger and Hyung (1999), Diebold and Inoue (2001), Liu (2000) are a few of many scholars who have done research in this light. This section continues in the same vein by considering two GARCH family models to investigate volatility behavior of these selected precious metals in the presence of oil and exchange rate shocks. With these models, we identify which amongst the precious metals has the highest (lowest) volatility persistence or convergence, and which has the longest (shortest) half-life duration in the event of shocks. Apart from being amongst the most traded commodities globally, the selected precious metals have several uses in art, jewelry, medicine etc., and have recently been favored as good investment assets. We also measure whether positive and negative shock impact divergently on their prices in lieu crisis or shocks. Furthermore, we are interested in finding out if there is any leverage effect on their volatility when there are positive and negative oil and exchange rate shocks.

As a major input in precious metal production, we also investigate whether oil has forward influences on commodity spot volatilities. Moreover, global oil supply is heavily regulated by OPEC and also affected by hurricanes, cold snaps, geopolitical events in oil producing countries etc. (Hammoudeh et al., 2007). In this section therefore, we use the GARCH (2, 2) model by Bollerslev (1986) and TGARCH (2, 2) models to analyze volatility persistence and convergence in these precious metals, and also measure the impact of positive and negative shocks on their returns. The results infer that precious metal producers, precious metal exporting countries, derivatives valuation and traders using gold as a reserve asset can carefully make informed decisions based on any prevailing market situation. Moreover, investors

looking for suitable diversifiers particularly during crisis can conclude on which precious metal to include or exclude from their portfolio in the short and long run if they understand how these process respond to positive and negative shocks in the market.

5.2 Literature Review

There have been numerous studies on volatility and efficiency in commodity markets. Oil price volatility has dominated this brand of research relative to other crude commodity prices (Reignier, 2007). Hammoudeh et al. (2004) investigated volatility persistence in the crude oil market and oil equity markets using both univariate and multivariate GARCH. After oil, they found that gold has attracted the most attention relative to other commodities. Using intraday and interday data, Batten and Lucey (2007) used univariate GARCH models to study volatility of gold futures contracts traded on the Chicago Board of Trade (CBOT). They provided interesting perceptions in the intraday and interday volatility dynamics of gold by examining the behavior of the futures returns and the alternative nonparametric Garman-Klass volatility range statistic (Garman and Klass, 1980). Furthermore, Ewing and Malik (2013) employed univariate and bivariate GARCH models to examine the volatility of gold and oil futures, they accounted for structural breaks and highlighted their findings by computing optimal portfolio weights and dynamic risk minimizing hedge ratios. Another study by Adrangi and Chatrath (2002) concluded that ARCH-type models with controls for seasonality and contractibility explained the nonlinear dependence in their data for palladium and platinum.

Volatility in stock prices and other commodity prices have been rampant in the last few decades particularly in wake of the 21st Century. Beginning with the 2000/2001

dot-com boom, followed by the 2007/2008 global financial crisis and the 2010/2012 European Union debt crisis, investors have become increasingly nervous as to where to channel their investments. Precious metal investments have become increasingly attractive as investors are still recovering from heavy losses from the mortgage crisis. Analyzing the volatility behavior of these very attractive precious metal investments would prevent investors from unprecedented losses due to historical shocks in the stock market.

O'Callaghan and Morales (2011) examine volatility persistence on precious metals returns taking into account oil returns and the three world major stock equity index (Dow Jones Industrials, FTSE 100, and Nikkei 225). They checked the resilience of precious metals returns in light of the global financial crisis and their findings provided a new guide for the investors considering precious metal investments. To compare unexpected changes in variance and volatility persistence in crude oil, Wilson et al. (1996) used the Ican-Tiao algorithm and the GARCH model. Tully and Lucey (2007) use the asymmetric power GARCH (APGARCH) model which nests the ARCH and GARCH models and account for the leverage and power effects. Their results confirm that the US dollar is the main if not the sole macroeconomic variable that influences gold volatility persistence when considering sudden changes in the variance of gold and the other precious metals. Batten et al. (2010) find that macroeconomic factors like financial market sentiments, monetary policy and business cycles affect volatility of gold, silver, platinum and palladium differently. They found gold to be highly sensitive to exchange rate and inflation, which makes it the best hedge during inflationary pressures and exchange rate fluctuations. Platinum and palladium apparently can be good financial market instrument than gold. In fact,

Hammoudeh, Malik and McAleer (2011) propose that expected future risks can be mitigated by including gold in optimal precious metal portfolios.

Although we do not investigate optimal portfolio weights for precious metal investments yet, we probe volatility convergence in relation to precious metals in the presence of oil and exchange rate shocks. We also investigate the asymmetric effect of good and bad news on these precious metal returns. Unlike the other studies, we use fairly extensive and high frequency data for the analysis. The findings are more robust given that we consider the AFC and GFC that must have significantly influenced expectations and thus investors' decision to include alternative precious metals in their portfolios for diversification reasons.

Therefore understanding the relative magnitude of volatility before investing is a key concern to risk averse investors. Portfolio managers looking for profit opportunities would find substantial value in understanding the volatility behavior of these commodities. Commodity options traders will be interested in knowing which commodity is the most volatile in the presence of unexpected innovations. Would it be better to invest in oil when oil prices are on the hike, or in precious metals? Or would it in effect be better to invest in both oil and precious metals instead of investing only in one set of commodities after a recession? From a policy stand point, would the effect of volatility be effectively managed if a tight monetary policy which would reduce commodity prices and lower expectations of rising inflation or a loose policy stabilize the economy? In addition, it would thought-provoking to see if there is some leverage effect of some strategic commodity's volatility and to identify the severity of the response to negative and positive shocks (Black, 1976; Nelson 1991;

Engel and Ng. 1993). Traders and policy makers are keen to get reliable responses to such questions, some of which this section of the thesis provides reasonable answers.

5.3 Methodology

We analyze volatility persistence in precious metal spot prices in the presence of and oil and exchange rate, and whether the impact differs during crisis periods. The crisis period considered are the Asian Financial Crisis (AFC) - July 2, 1997 to December 31, 1998; and the Global Financial Crisis (GFC) - August 7, 2007, to December 31, 2008 which are represented by two respective dummy variables ‘ $D1$ ’ and ‘ $D2$ ’ (Aliyu and Rano, 2009). The dummy variables are set to take the value of 1 during the crisis and 0 otherwise. Tables 1 and 2 summarize the descriptive statistics and correlation matrix respectively for all the variables. The kurtosis, skewness and Jarque-Bera results are indicative of non-normality of the series. The series has fat tails (leptokurtic) thus suggesting the autoregressive heteroskedasticity (ARCH) test. A further performance of the ARCH test suggests the appropriateness of the GARCH-type model.

Alternative unit root tests (see Table 4) are performed to check for stationarity in the data. The first difference of the log returns are used instead of the levels because the level data is non-stationary. The co-integration test results (see Table 5) reveal the series follows an $I(1)$ process as shown by the Johansen (1995) co-integration test and the Stock Watson (1988) tests. Furthermore, the ARCH²⁷ LM test shows a significant ARCH effect thus advocates the appropriateness of ARCH-type models for forecasting their time-varying conditional volatility. Our methodology follows the pioneers works orchestrated by Bollerslev (1991) regarding the joint estimation

²⁷ This check is done both prior and post model estimation to certify that no ARCH effect lingers in any of the models for any of the commodities.

of the conditional mean and conditional variance equations to investigate volatility behavior of financial time series. The ARCH test must be done pre and post estimation to ensure that the ARCH effect does not linger after the estimation. However if the ARCH effect lingers post estimation, then it is implicit of misspecification of the variance equation. In addition, we investigate the impact of both positive and negative shocks on the conditional variance since it is important to verify asymmetry given the data. What makes asymmetric GARCH models interesting is their ability to capture some stylized facts that are ignored by the standard GARCH model which imposes a the non-negativity constraint. With asymmetric GARCH models, we can investigate whether positive and negative shock impact similarly or otherwise, and whether there may be a leverage effect or not.

5.3.1 The Standard GARCH Model

To investigate volatility persistence and convergence, different volatility models of the GARCH family are estimated. Based on the maximum likelihood estimations and Akaike Information Criterion, the GARCH (2, 2) is most suitable amongst the GARCH (p, q) models tested. The mean equation for the estimated GARCH model is as follows:

$$r_{it} = \pi_{0i} + \pi_{1i}Z_{it} + \varepsilon_{it} \quad (8)$$

$$DLdep_{it} = \pi_{i,t} + \pi_{1i}DLdep_{i,t-1} + \pi_{2i}DLWTI_{t-1} + \pi_{3i}DLER_{t-1} + \varepsilon_{it} \quad (9)$$

where $DLdep_{it}$ and $DLdep_{i,t-1}$ are the returns and lagged returns of any precious price between day ' t ' and day ' $t-1$ ', π_{0i} is the long-term drift. Z_{it} represents exogenous variables while $\varepsilon_{it}|I_{t-1} \sim N(0, \sigma_{it}^2)$; where $N(.)$ is the conditional normal density with zero mean and variance σ_{it}^2 , and I_{t-1} is all the information set available up to the period $t-1$. The variance equation for the i -th commodity is given by:

$$\sigma_{it}^2 = \omega_i + \sum_j \alpha_{ji} \varepsilon_{it-j}^2 + \sum_k \beta_{ki} \sigma_{it-k}^2 + \psi_{1i} DLWTI_{t-1} + \psi_{2i} DLER_{t-1} + \psi_{3i} D1 + \psi_{3i} D2 \quad (10)$$

The subscripts i stands for any of the precious metals, $DLWTI$ and $DLER$ stand for changes in oil returns and exchange rates between two consecutive periods. $D1$ and $D2$ represent the two dummies for the Asian Financial crisis and the Global Financial crisis respectively. Other structural dummy variables for the 2001 dot-com boom and 2003 Iraq war were also tested but showed lesser significance. In Eq. (10), σ^2 is the conditional variance and its lags and are the GARCH terms, ε_j^2 is the squared residuals of the mean equation, which represents the j -th ARCH term. The coefficient β_{ki} is the k -th GARCH term or volatility effect while α_{ji} captures the j -th ARCH or past shock effect and j and k denote the number of lagged ARCH and GARCH respectively. The sum of $\sum (\alpha_{ji} + \beta_{ki})$ measures the degree of convergence to long-run equilibrium or volatility persistence for commodity i in the model. If the sum approaches 1, it is said to manifest high volatility persistence otherwise slow convergence.

5.3.2 The Threshold GARCH (TGARCH) Model

Unlike the canonized GARCH model (Bollerslev, 1986); special GARCH-type models have been developed to capture stylized facts in financial time series. The TGARCH model, the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model and Exponential GARCH (EGARCH) are designed to assume specific parametric forms for conditional heteroskedasticity. Black (1976) found that when forecasting volatility, an unexpected decrease in prices projects a stronger impact than when there are unexpected increases in prices or returns. He referred to these positive and negative events as good and bad news and found that their effects on volatility were

not symmetric. Bad news significantly produces a more dramatic impact on volatility than good news. In finance, this is termed “leverage effect” and this asymmetric effect can be estimated by using the any of the above mentioned specific GARCH family models. French (1987) and Nelson (1991) confirmed this and asserted that standard generalized ARCH models may be weak in apprehending asymmetric impact of different types of news as a result of the non-negativity constraints of the signs of the coefficients. The general formulation of the TGARCH model assumes a mean equation similar to Eq. (8) while the variance equation takes the form;

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta \sigma_{t-j}^2 + \sum_{k=1}^r \delta_k \varepsilon_{t-k}^2 I_{t-k} \quad (11)$$

where
$$I_{t-k} = \begin{cases} 0 & \text{if } \varepsilon_t \geq 0 \\ 1 & \text{if } \varepsilon_t < 0 \end{cases}$$

The parameters ω , α , δ and, β are empirically estimated by maximum likelihood, σ_t^2 is the conditional variance, the innovation ε_t is assumed to be drawn from a conditional normal distribution with zero mean and variance σ^2 . I_{t-1} represents all information available up till the time $t-1$. Regardless of the consideration of the conditional distribution as Gaussian, it can be proven that their unconditional distributions fat tailed (leptokurtic). Like the standard GARCH model, the TGARCH model is capable of capturing stylized facts in financial time series such as volatility persistence and clustering. Volatility is more likely to be high at any given time t if it was also high at time $t-1$. Alternative, shocks at time $t-1$ are more likely to impact on the variance at time t .

With the TGARCH model, it is possible to deduce pertinent facts about financial time series. It can be shown that the impact of positive and negative shock impact

asymmetrically on the returns of financial assets - with negative shocks exhibiting a stronger impact than positive shocks. This asymmetric effect is known as the ‘leverage effect’ since the increase in risk is triggered by increased leverage due to a negative innovation (shock). The best model is selected TGARCH (2, 2) using the AIC with $p=2$ and $q=2$. The effective impact of the negative shock is seen to be $\Sigma(\alpha + \delta)$ with δ commonly seen to be statistically significant in financial time series. If $I_{t-1} = 0$ in Eq. (11), then the model collapses to a standard GARCH model. The TGARCH (2, 2) model is used for the analysis based on AIC, ARCH-LM test.

5.3.3 The Exponential GARCH (EGARCH) Model

As earlier mentioned, the dynamic impact of good and bad news can be explained using several asymmetric GARCH models. The Exponential GARCH model (EGARCH) introduced by Nelson (1991) is one of such models which relaxes this non-negativity constraint prevalent with the standard GARCH model. In the EGARCH model, the specification of the mean equation is similar to Eq. (8) but the variance equation is uniquely expressed as:

$$\log \sigma_{it}^2 = \omega_i + \sum_j \beta_{ji} \log \sigma_{it-j}^2 + \sum_k \alpha_{ki} \left| \frac{\varepsilon_{it-k}}{\sigma_{it-k}} \right| + \sum_k \delta_{ki} \frac{\varepsilon_{it-k}}{\sigma_{it-k}} + \tau_1 WTI_{t-1} + \tau_2 ER_{t-1} + \tau_3 D1 \quad (12)$$

The left-hand side of the variance equation permits the equation to be negative since it is in log form. This prompts the effect of positive and negative shocks to be different on the log of the conditional variance. The drift of the variance equation is ω_i while α_{ki} is the size effect and measures the magnitude of the change in volatility regardless of the direction of the shock. β_{ji} captures the persistence of the shock

while δ_{ki} is the sign effect²⁸. The term $\frac{\varepsilon_{it-k}}{\sigma_{it-k}}$ stands for the standardized value of the k^{th}

lag residual and eases interpretation of the magnitude and persistence of both positive and negative shocks. If the coefficient $\delta_{ki} \neq 0$ and significant, the impact of the shock will be asymmetric implying different effects of positive and negative shocks. On the other hand, if $\sum \delta_{ki} < 0$ and significant, then the leverage effect is considered present. As such, the asymmetric effect is represented by the term $\frac{\varepsilon_{it-k}}{\sigma_{it-k}}$.

The k -th symmetric effect is represented by the term $\left| \frac{\varepsilon_{it-k}}{\sigma_{it-k}} \right|$. If the shock is positive, implying $\frac{\varepsilon_{it-k}}{\sigma_{it-k}} > 0$, the impact on the conditional variance will be measured as $\Sigma (\alpha_{ki} +$

$\delta_{ki})$. Conversely, a negative shock is implicit of the leverage effect and its impact will be measured by $\Sigma (\alpha_{ki} - \delta_{ki})$. Several other extensions of asymmetric GARCH models exist but we use the TGARCH model because of its compatibility with our data set based on the AIC and LR test.

5.4 Results and Discussion

As earlier mentioned, all the series are non-stationary and the results of the stationary tests favor the first difference of the variables (see Table 4). Co-integration tests are summarized in Table 5 and show that the variables are I (1). Diagnostic tests were performed and the results show no serial correlation of residuals. The kurtosis, skewness and Jarque-Bera results are indicative of non-normality of the series as is the case with most financial series. The variables have fat and leptokurtic tails which

²⁸ As stipulated by Nelson (1991), a $|\beta_{ji}| < 1$ guarantees mean reversion and ergodicity for the GARCH (p, q) model, while δ_{ki} indicates whether the shock's impact is asymmetric or symmetric. If δ_{ki} is positive, it implies that a positive shock has a larger impact on volatility than a negative shock and vice versa

is common with financial time series and prompts the use of GARCH-type models for the estimation. Two exogenous variables (dummy variables D1 and D2) are included in the variance equation to represent the AFC and GFC respectively.

The standard GARCH (1, 1) was the initial starting point for the estimation process but the ARCH-LM test revealed that the ARCH effect lingered after estimating the GARCH (1, 1) model. This signaled misspecification of the variance equation hence a precursor to estimate higher order GARCH models. After testing many GARCH (p , q) models, the GARCH (2, 2) and TARCH (2, 2), otherwise known as the GJR-GARCH (2, 2) were selected from decisions provide by the AIC and the Log Likelihood tests. Performing the ARCH test post model estimation also favored this model. The GARCH (2, 2) model results are summarized on Table 8.

The results indicate that all four precious metals are sensitive to past shocks and past volatilities at a 5% significance level. Moreover, there is high persistence or otherwise slow convergence in volatility for gold, silver, platinum and palladium in that order. This infers that convergence to long-run equilibrium is slower for gold and silver – which have a higher monetary and investment potential, than for platinum and palladium which are basically industrial commodities. Fundamentally, gold and to a lesser extent silver, are investment asset rather than industrial metal which are resistant to adverse market shock, and adjusts more quickly to their long-run price levels than the other precious metals. The demand for gold is influenced largely by jewelry demand and recycling. Moreover, gold is considered a “safe haven” during crisis, and hence more resistant to adverse shocks.

Table 8: GARCH (2, 2) - Impact on metal returns and volatility due to oil and exchange rate shocks

	Gold		Silver		Platinum		Palladium	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Constant	-1.03E-05 (-0.12)	2.71E-08*** (3.60)	-6.52E-05 (-0.39)	4.11E-07*** (5.55)	0.000213 (1.59)	8.28E-07*** (5.52)	2.64E-04 (1.48)	1.67E-05*** (19.81)
Dep. Var(-1)	-0.025512* (-1.78)		-0.023109* (-1.73)		-0.040680** (-2.83)		0.020438 (1.62)	
Oil Shock	0.018334*** (4.326)	7.56E-06*** (3.72)	0.026034*** (2.98)	9.39E-07 (0.11)	0.026439*** (3.59)	-5.10E-05*** (-3.26)	0.032402*** (4.05)	-8.99E-05* (-1.78)
ER Shock	0.035294** (2.53)	2.12E-05*** (3.97)	0.001273 (0.47)	0.000118 (5.11)	0.130851*** (5.92)	0.000154*** (3.33)	0.053085* (1.95)	0.000709*** (8.41)
Dummy AFC		3.15E-08 (1.44)		5.45E-07** (2.45)		8.21E-07* (1.92)		1.76E-05*** (3.11)
Dummy GFC		3.47E-07*** (3.28)		2.53E-06*** (6.12)		4.15E-07 (1.23)		1.65E-06 (0.60)
α_1		0.085413*** (15.76)		0.118627*** (15.55)		0.160401*** (16.32)		0.115777*** (28.08)
α_2		-0.078308*** (-15.93)		-0.107179*** (-15.41)		-0.128259*** (-13.74)		0.106992*** (26.11)
β_1		1.705066*** (43.11)		1.489902*** (30.49)		1.247254*** (16.06)		-0.113236*** (-24.59)
β_2		-0.712355*** (-18.67)		-0.503085*** (-10.54)		-0.283109*** (-3.89)		0.859256*** (179.77)
LL	22143.17		18161.47		19522.53		17303.76	
DW	1.981817		1.923099		1.990360		1.972653	
AIC	-6.749061		-5.534756		-5.949842		-5.273180	

Note: Oil shock defines the first difference in oil return. LL stands for the log likelihood. AIC denotes the Akaike Information Criterion. D1 and D2 are dummies for the AFC and GFC respectively. The values in parenthesis are the Z-statistics. ***, **, * represent significance at 1%, 5% and 10% levels respectively.

Silver is partly a precious metal and an industrial metal which adjusts somewhat quickly as well. On the other hand, the closer industrial metals platinum and particularly palladium converge more rapidly to their long run equilibrium. This bears strongly when considering the half-life values with palladium converging about 172 time faster than gold but just about 8.5 times faster than palladium (see Table 11). These results are consistent with those of Hammoudeh and Yuan (2007) who inferred lower volatility persistence for copper than for gold and silver. They show that the rapid convergence to long-run volatility is traced mainly in the transitory rather than the permanent component of volatility.

Table 9: TGARCH (2, 2) - Impact on metal returns and volatility due to oil and exchange rate shocks

	Gold		Silver		Platinum		Palladium	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Constant	0.000101 (1.16)	2.71E-07*** (6.5.19)	0.000159 (0.94)	7.10E-07*** (5.66)	0.000306** (2.31)	8.05E-07*** (-5.39)	0.000262 (1.31)	9.30E-06*** (7.25)
Dep. Var. (-1)	-0.025380* (-1.75)		-0.026937* (-1.92)		-0.022989 (-1.61)		0.021271 (1.55)	
Oil Shock	0.018749*** (4.13)	3.48E-05*** (3.50)	0.024288*** (2.88)	-4.94E-06 (-0.41)	0.061819*** (8.91)	-4.83E-05*** (-3.34)	0.062421*** (6.90)	-0.000223*** (-4.126)
ER Shock	0.026815* (1.91)	-6.17E-05* (-2.89)	-0.000254 (-0.01)	0.000110*** (3.07)	0.312399*** (16.14)	0.000128*** (2.86)	0.374277*** (14.64)	-0.000311** (-1.97)
D1		4.50E-07*** (2.16)		6.99E-07* (1.92)		8.71E-07** (2.02)		7.41E-06** (2.15)
D2		2.06E-06*** (3.14)		5.16E-06*** (7.41)		5.51E-08 (0.19)		1.01E-06 (0.77)
β_1		0.656255*** (5.45)		1.303498*** (18.52)		1.266249*** (16.25)		0.689102*** (4.99)
β_2		0.290427** (2.52)		-0.324785*** (-4.78)		-0.302469*** (-4.16)		0.173725 (1.44)
α_1		0.092668*** (11.86)		0.128911*** (12.26)		0.168317*** (13.54)		0.162722*** (11.45)
α_2		-0.008723 (-0.70)		-0.095971*** (-9.11)		-0.122412*** (-10.27)		-0.034537 (-1.64)
δ_1		-0.021565* (-1.75)		-0.047982*** (-3.60)		-0.024171 (-1.50)		-0.014486 (-0.74)
δ_2		-0.042091*** (-3.38)		0.020063 (1.46)		-0.000440 (-0.29)		-0.004794 (-0.27)
LL	22182.45		18211.04		19646.27		17381.89	
DW	1.979985		1.915383		2.066918		1.970113	
AIC	-6.760431		-5.549265		-5.986360		-5.296399	

Note: Oil shock defines the first difference in oil return. LL stands for the log likelihood. AIC denotes the Akaike Information Criterion. D1 and D2 are dummies for the Asian financial crisis and global financial crisis respectively. The values in parenthesis are the Z-statistics. ***, **, * represent significance at 1%, 5% and 10%, respectively.

The TGARCH (2, 2) results (see Table 9) reveal some interesting findings on the asymmetric effect of positive and negative shocks on the different precious metal returns. This impact is more significant for gold and silver where the asymmetric terms are negative and significant. Gold and silver are sensitive to good news such as increase in jewelry demand, and rise in industrial demand for silver. This may account for the relatively steeper positive slope of the News Impact Curve²⁹ (NIC) for both gold and silver ((see Fig. 9). The slope is flatter in the case of a negative shock because both gold and silver are known to have safe haven properties and investors rush to invest in them in crisis periods and periods of high expected

²⁹ Pioneered by Pagan and Schwert (1990), the NIC plots the next-period volatility (σ_t^2) that would arise from various positive and negative values of u_{t-1} , given an estimated model

inflation. Nonetheless, the NIC for silver has a steeper negative slope than for gold thus highlighting that silver is more sensitive to crisis or negative shocks relative to gold. This consensus is in line with previous researchers who assert that silver has lost some of its monetary element and has become a vital industrial commodity.

Table 10. Summary of Results

	GARCH(2, 2)				TGARCH(2, 2)			
	$\alpha_1 + \alpha_2$	$\beta_1 + \beta_2$	$\alpha_1 + \alpha_2 + \beta_1 + \beta_2$	HalfLife	$\alpha_1 + \alpha_2$	$\delta_1 + \delta_2$	Shock(+) $\alpha_1 + \alpha_2 + \delta_1 + \delta_2$	Shock-($\alpha_1 + \alpha_2$) $ + \delta_1 + \delta_2$
Gold	0.0071	0.9927	0.9998	3766.758	0.0839	-0.0637	0.0203	-0.1476
Silver	0.0114	0.9868	0.9983	399.162	0.0329	-0.0279	0.0050	-0.0609
Platinum	0.0321	0.9641	0.9963	186.334	0.0459	-0.0246	0.0213	-0.0705
Palladium	0.2228	0.7460	0.9688	21.860	0.1482	-0.0393	0.1089	-0.1876

Note: The orders of the ARCH and GARCH terms are taken from post estimated ARCH tests. In the GARCH (2, 2), while α_1 and α_2 consist of a measure of cumulative past shocks, β_1 and β_2 stand for cumulative past volatility effect. In the TGARCH (2, 2), if $\sum (\delta_1 + \delta_2)$ is negative, then the leverage effect is present and if it is significant then there is an asymmetric effect. The half-life is computed by the

formula: $\frac{\ln(\frac{1}{2})}{\ln \sum (\alpha_i + \beta_i)}$

Although negative, the asymmetric terms in the TGARCH (2, 2) model are insignificant for platinum and palladium. Regardless of the presence of the leverage effect, it is however not significant for platinum and palladium as it is for gold and silver. This may infer that good and bad news impact somewhat indifferently on these metals. The NIC for platinum clearly shows no significant distinction between the impact of good and bad news. Palladium's NIC is somewhat symmetric around the origin thus accounting for similar effects of the impact of good and bad news. As such, the impact of good and bad news is not the same on all the precious metals thus accounting for asymmetric effect of positive and negative news. Table 10 summarizes the TGARCH (2, 2) results while Table 11 presents a summary of both GARCH model.

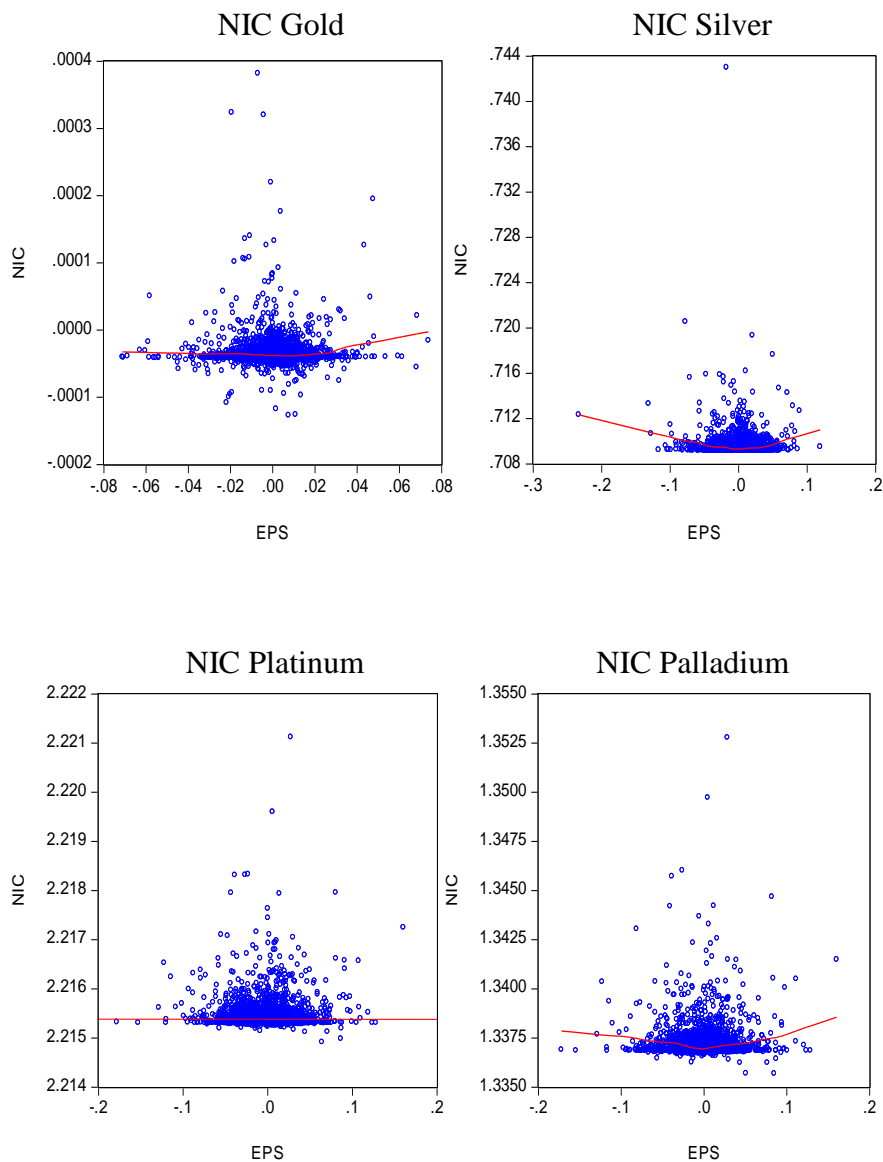


Figure 9: News Impact curves for Gold, Silver, Platinum and Palladium

Note: The curves shows next-period volatility that would arise from various positive and negative shocks given out estimated model.

As earlier discussed, oil is the most volatile commodity and has the fastest speed of convergence when affected by shocks like hurricanes, refinery outages, cold snaps, geopolitical factors in major oil producing nations etc. Moreover, the oil market is heavily influence by the OPEC cartel. These factors accelerate oil volatility relative to the precious metals as such, oil shock impact dissimilarly on the precious metals. Some investors may switch from metal to oil investments when there are positive oil shocks. This may decelerate precious metal volatility. However, the industrial metals

may not be good replacements for oil in portfolio management. Rising exchange rate shocks heighten metal price volatility like the GFC and AFC.

5.5 Conclusion

On exposure to similar macroeconomic variables, financial crisis, oil and exchange rate shocks, precious metals show dissimilar levels of volatility persistence. For instance, gold and silver sometimes experience exceptionally high demand for hoarding purposes from emerging economies like China, India, Russia and the Middle East generate due to cultural reasons. This section of the thesis measures volatility behavior of our selected precious metals in the presence of oil and exchange rate shocks. We tread distinctly from some previous research by using two GARCH family models with extensive and recent data, and investigate the impact of positive and negative news on volatility.

Amongst the precious metals, the industrial metals have high convergence to long-run equilibrium in their conditional variance when compared to gold and silver which are considered as investment asset. This solicits the interest for options traders particularly to accurately measure and predict the value of financial derivatives in which these precious metals are the underlying assets. The AFC only had significant impact on silver and palladium at a 5% level of significance. The impact on gold is insignificant accounting for gold being a resistant asset in crisis periods. Conversely, the GFC significantly affected the investment metals (gold and silver), and not platinum and palladium. This result may account for the fact that, investors may have included gold and silver in their mortgage portfolios which resulted to the significant impact of the GFC on these precious metal returns when the housing burble ruptured. The fact that the GFC did not significantly affect platinum and palladium implies that

they could be useful as good diversification assets for hedgers. The AFC seemingly did not significantly affect gold and silver prices thus presenting them as safe assets during crisis periods. Access to such timely information would benefit traders and portfolio managers in reaping profit as compared to their more ignorant counterparts.

The TGARCH results suggest significant asymmetries in the effect of good and bad news. Therefore precious metals present themselves as suitable investment assets during crisis and periods of rising levels of uncertainty. Central banks and countries that use gold as their primary reserve asset, as well as precious metal exporters who depend on the revenue, will also benefit from the results of this study. The negative impact of oil shocks on some precious metals' volatility provides benefits to portfolio managers when designing options and can find opportunities in the precious metal market.

The impact of good and bad news is asymmetric for gold and silver as shown by their negative and significant asymmetric terms. As previously mentioned, rising jewelry demand as well as unprecedented increases in the industrial demand for silver increase volatility. This can be interpreted as the relatively steeper positive slope of the NIC's for both gold and silver with silver's reaction being more pronounced because its safe haven properties have been lost to its industrial appeal. For the more industrial platinum and palladium, as shown by their NIC's, platinum exhibits indifference between good and bad news. Palladium has a somewhat symmetric effect on news.

These results present viable options for smart investors, to make informed investment decisions on which precious metals to invest at different times, and also

to make reliable future forecasts in expected returns. Hedgers would realize that in case of crashes in the commodity market, gold and sometimes silver may be the next best alternative investment to adhere to, while palladium maybe a good diversifier during crisis.

Chapter 6

CONCLUSION

Considering that precious metal prices tend to move in tandem when exposed to akin macroeconomic variables, in this thesis, I aimed to probe the information transmission dynamics of these precious metals prices while accounting for oil and exchange rate shocks. To attain this objective, this study was divided into three principal sections; first, to analyze information transmission dynamics before and after the GFC; second, to ascertain nonlinearity in the prices in when exposed to structural breaks in multiple regimes; and finally to measure persistence, convergence and asymmetry in the volatility performance of these prices while accounting for oil and exchange rate shocks.

In the first section, the points of interest included looking for the key price drivers amongst the precious metals, which commodity's price was most informative and which commodity could be a good hedge asset before and after crisis. Using the VECM, the short and long term relationship amongst the precious metal prices is examined. Gold and silver have the highest historical correlation (95%), closely followed by oil and platinum (94%), thus suggesting the former pair as close monetary and investment assets, while the latter pair as close industrial neighbors. As opposed to the findings of some researchers, I found that the extent to which gold price changes affect silver price returns greatly surpass the way in which silver prices impact on gold price returns. It was also found that gold and platinum had the lowest

standard deviation which presents gold as an inflationary hedge and platinum as an investment asset diversifier which recently moves in a lock-up with gold.

Oil and palladium showed the highest historical standard deviation. For oil, this high volatility could be accounted by the fact that oil is the prime energy source in precious metal production. Its price is highly sensitive to the geopolitical atmosphere of the major producers, hurricanes, refinery outages etc. The high historical correlation with oil may be due to the forward and backward uses in many sectors of any economy. Post crisis, increases in oil prices may imply a rise in the short-term silver, platinum and palladium prices due to their extensive industrial uses. Palladium is seen to have the lowest historical correlation, and its price changes do not explain any of the changes in the other commodities. This makes palladium a good hedge asset for investors with a precious metal portfolio. Furthermore, although platinum and palladium derive their demand from the automobile industry, a unidirectional relationship exists between changing platinum prices which highly affect variances in palladium prices.

With respect to nonlinearity and information transmission in a regime-switching environment, the data for the MS-VEC reveals the existence of two regimes (low volatility and high volatility) with substantial asymmetries. The initial and subsequent effect of increases in the gold price on the other variables is positive and significant in the both regimes, but the effect dampens in the high volatility regime. Although, in the high volatility regime the gold impact on the US dollar/euro exchange rate is initially negative (i.e., dollar first appreciates), it later becomes positive (i.e., depreciates and becomes less valuable) because the fluctuations in prices may transmit negative expectation about future inflation. Like the results in

the previous section, changing gold prices impact most significant on silver prices, while the impact of those changes is the lowest for oil. Again, a viable explanation may be that gold and silver share similar features as monetary and investment assets, while gold and oil are mainly related in the long run because of their diverse uses.

An interesting finding is that palladium prices depress exchange rate (appreciating US dollar and depreciating the euro) in both regimes and the gold price in regime 2. This possibly may be due to a temporary loss of the hedging property of palladium. On the other hand, changes in the exchange rate affect all commodities significantly because they are all traded in US dollars. Both currencies serve as the major link to all the commodities because they are the two major currencies used for trade and other international exchanges. The changes in the exchange rate since 2000 result from the weakening dollar thus causing substantial spiking in commodity prices.

Regarding volatility behavior of precious metals, there is slow convergence or high persistence for the investment and monetary assets (gold and silver) than the more industrial commodities (platinum and palladium). Gold and silver therefore adjust more quickly to shock than their industrial counterparts. In addition, gold and silver portray asymmetry in good and bad news on the conditional variance. Even though gold and silver exhibit resistant to the AFC, silver is a lot more vulnerable than gold as seen by the NIC. This may be a result of the lost monetary element of silver which has become more of an industrial than a monetary unit over the past decades. Gold and silver show some leverage effect while platinum and palladium show and insignificant leverage effect.

From the outcomes above, it is recommended that international investors consider including palladium in their precious metal portfolios since its low correlation makes it a good hedge asset. Particularly during high volatility regimes, investors of precious metal, central banks and other stakeholders should watch gold and oil prices carefully especially due to their high information content in determining the direction of change in the other commodity prices and exchange rate. Changes in the gold and oil prices can determine the direction of exchange rates. Therefore central banks and governments can implement better policies to serve as a cushion especially during periods of high volatility. Moreover, investors can make reliable forecasts in different regimes regarding investing in precious metals. Hedgers will turn to gold and maybe silver particularly during crisis while using palladium as a portfolio diversifier. Consumers' purchase decisions for durable goods would be more accurate if they understand the relationship between the commodities since these durables are made from some of these metals. Major oil importers/exporters as well as oil traders may benefit from these findings by monitor oil price changes especially post crisis.

Investors and speculators should watch the changes in the gold price carefully as a change in direction may suggest whether to invest in silver or not. For the oil-importing and exporting countries, monitoring oil prices particularly in the high volatile regime is vital since it can act as a barometer to governments on how to implement effective policies to stabilize their exchange rates, inflation and balancing the budget.

Further extensions of this research will be geared towards attempting to derive the optimal portfolio weights that would maximize return in a pure precious metal

portfolio. It would be thought-provoking to ascertain whether the derived optimal portfolio weights for a portfolio of uniquely precious metal, would yield a higher return than a similar portfolio having oil as one of its assets. Ewing and Malik (2013) did a similar analysis but restricted it to gold and oil prices. An extension to this research would provide a clear dichotomy on what proportion of different combination of low risk-high return assets to include in an efficient portfolio of precious metal, and a case with oil included. In addition, performing an out of sample forecast for these precious metal prices would be also vital and my guide investment decision during periods of both high and low expected inflation. It would aid producers of these precious metals to develop policies that mitigate risk when expectations of low returns are high, and to maximize returns when market conditions are favorable.

Furthermore, for precious metal and oil importing and exporting countries, it would be stimulating to know to what extent monetary policy can influence these commodity prices. Would there be a boost in these commodity prices when these country's central banks operate either a tight or loose monetary policy? Moreover, to what extent does this impact on economic growth and income distribution? As in many countries that produce these raw commodities, e.g. gold (South Africa and China), palladium (Russia) etc., there is almost always inequitable resource allocation to foster development. Often, the districts in which the mines are located are the poorest regions of the respective countries. It would be good to understand why this phenomenon is common worldwide and look for ways to bridge the gap. As such, policies that would benefit both the miners and the areas in which these mines are located could be implemented.

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