ESSAYS ON COMMODITY PRICES AND ECONOMIC ACTIVITY
IN A RESOURCE RICH COUNTRY

by

EUGENIO MARIA PAULO

B.Com./B.Ec., The Australian National University, Canberra, 2002

M.A., The University of Kansas, 2010

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

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Abstract

The increase in commodity prices that has taken place in the past decade or so has resulted in renewed interest in the debate about the macroeconomic consequences of such price increase. Previous studies tend to assume that all commodity price shocks are alike and advocate a "one size fit all" policy response by monetary authorities, either by means of contractionary monetary policy to alleviate inflationary pressures or doing nothing, since these shocks are believed to have insignificant economic impact. This dissertation analyses the impact of fluctuations in commodity prices on the South African economy. The first chapter studies the impact of shocks to prices of four commodities on monetary policy variables. Results show that shocks to different commodity prices have different effects on the monetary policy variables, hence rejecting the "one size fits all" policy response by monetary authorities, as some researchers have suggested.

Chapter two investigates the sectorial effects of commodity price shocks. The Dutch Disease hypothesis suggests that a boom in the natural resource sector shrinks the manufacturing sector through crowding out and appreciation of the real exchange rate. South Africa is a major exporter of a large number of commodities. Using a structural VAR framework this chapter analyzes the impact of shocks to different commodity prices on the production and employment levels in the manufacturing and mining sectors in South Africa. The results show that the commodity price boom has had a positive impact on both sectors, hence the manufacturing sector did not experience signs of the Dutch disease.

Chapter three examines the volatility transmission between commodity prices and nominal exchange rate in South Africa. This chapter uses conditional and realized volatility models to estimate volatility in exchange rate, gold, platinum, oil, palladium and silver prices and then employs Granger-causality, Impulse Response analysis, Variance Decomposition and Ordinary Least Squares to analyze the volatility transmission from the commodity prices to the nominal exchange rate. The results show that there is volatility transmission from commodity prices to the nominal exchange rate, hence knowing the volatility in commodity prices would improve investor's ability to manage risk in South Africa.

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Major Professor
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Dedication

I dedicate this work to my parents, siblings, wife, and my children Victorino, Mariana and Rabia for their trust and encouragement, without which this research would not be possible.

Chapter 1 - The Impact of Commodity Price Shocks on Monetary Policy in South Africa

1.1 Introduction

The increase in commodity prices that has taken place in the past decade or so has resulted in renewed interest in the debate about the macroeconomic consequences of such price increase. Fluctuations in commodity prices are widely believed to have economic implications for both developing as well as advanced economies, commodity importing as well as commodity exporting countries alike. Given the effect that commodity prices have on the economy, not surprisingly, a question that arises is how policymakers should respond to such price increases. The debate over the policy implication of increase in commodity prices has not been settled in the literature. This study analyzes the Monetary Policy impact of commodity price fluctuation in a small open, and resource rich country.

Over the past decades, the conduct of monetary policy has evolved considerably. New policy strategies have been tried and new policy targets have been in place as economists learned about the inability of the old strategies to work according to the theoretical prediction (Angell, 1992). In recent years however, there seems to be a consensus among economists that price stability should be the goal of Monetary Policy. Despite this agreement on the overall goal of the Monetary Policy, the debate about the right procedure and instrument to achieve the price stability has not been settled. One of the instruments that has been contemplated to help achieve the price stability are the commodity prices.

Commodities are used as inputs in the production process, hence the conventional wisdom is that other things being equal, an increase in commodity prices would lead to an increase in the general price level, such as consumer price index[1]. Those who embrace this view would advocate for the need for policymakers to monitor the commodity prices closely since increase in these prices would be an indication of future inflationary pressure. For instance, Furlong (1989) observed that commodity prices can help improve inflation forecasting, and consequently they can be useful for the conduct of monetary policy.

[1] See for instance Boughton and Branson (1988); and Malik and Ricardo (2013).

However, an increase in commodity prices may also lead to higher cost of production, which, other things being equal will have a negative effect on the production level. For instance, Hamilton (1983) finds that most of the US recessions between 1945 and early 1980s were preceded by an increase in oil prices, and Jones et al. (2004) finds that for a 10% increase in oil prices from 1945 to 2001 was associated with a loss in US real GDP by 0.5% after two years. So, the Monetary Policy implication of this view would be to implement expansionary policy as a way to counteract the negative effect of the increase in commodity prices on the production level, which is the opposite policy that would be required to assuage inflationary pressures that the increase in commodity prices may cause.

The two stances above illustrate the complexity of using commodity prices as a monetary policy indicator. In the event that increase in commodity prices lead to inflationary pressure and slowdown in economic activity, the use of monetary policy will yield conflicting outcomes. This complexity of the effect of commodity prices on economic variables is one of the reasons that makes some economists believe that the monetary authorities should not use commodity prices in their policy formulation. For example, Cody and Mills (1991) find that although if the fed took into account the changes in commodity prices in the monetary policy decisions would significantly impact inflation and output dynamics, but in reality the fed made its policies without using the commodity prices. Bernanke et al. (1997) in trying to explain the decline in the US economy following an increase in the oil prices argue that the large negative effect of the oil price shock on the US economy is not the result of the oil shock per se, but rather it is a result of the contractionary monetary policy used by the Federal Reserve in response to increase in oil prices.

Another issue that has been raised in the literature which makes it difficult to use commodity prices for monetary policy formulation is the persistence[2] of the commodity price shocks. If changes in commodity prices are caused by temporary disturbances, policymakers are less likely to respond with monetary policy since monetary policy's role is to control long-term inflation and not temporary increase in price level. Given the monetary policy lags[3] by the time the policy response has its effect, the problem would have gone away. Any actions by the monetary authorities would create more problems to the economy. For instance, Blinder and Reis (2005)

[2] For more detail see Cashin et al. (2000), Cashin and McDermott (2002) and Ghoshray (2013).

[3] See Friedman (1961).

find that during the Greenspan era, changes in food and energy prices tended to be transitory rather than permanent, which explains why commodity price did not matter in the monetary policy formulation. So, determining the persistence of the commodity price shock is very important in determining if a policy response is necessary at all.

From a commodity exporting country, increase in commodity prices could be expected to have positive effects to the economy, since other things being equal, higher commodity prices could be reflected in higher export revenues, hence higher output. Higher commodity prices can also have a negative effect on some sectors of a commodity exporting, especially if the higher commodity prices cause an appreciation of the exchange rate. For instance, Plumb et al. (2013), find that although the recent resource boom has led to a strong growth in the Australian resource sector, the output of certain sectors that do not supply many inputs to the resources sector have declined.

Commodities play a very important role in South African economy. Commodities are so important in South African economy that its currency is one of world's commodity currencies[4]. According to the Chambers of Mines 2012 report, South African mining industry is the fifth largest in the world. Among the various mineral commodities that the country exports, the platinum group of metals, gold, coal and iron ore have been the main ones in terms of sales and employment, Antin (2013). According to UNCTAD (2012), the increase of gold prices and other minerals, have had a positive impact on the South African terms of trade since 2004. Furthermore, this positive impact on South African terms of trade exceeded the combined negative effects of rising oil prices and adverse movements in the prices of imported manufactures. Agricultural commodities are also very important in South African economy. The country is a net exporter of food and other types of agricultural commodities. Agricultural commodities are also very important inputs in the local manufacturing sector.

Because of the large percentage of South African GDP coming from commodity exports, commodity prices in South Africa play a very important role in affecting income, production and employment. Commodities are also used as inputs in the local manufacturing sector. Therefore,

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[4] Commodity currency is a label assigned to currencies of economies that depend heavily on the export of certain raw materials. See Chen and Rugoff (2002); Groen and Pesenti (2009).

from the earlier analysis, increase in commodity price could be expected to have effect on the production level as well as on the general price level.

Despite this importance that commodities play in South African economy, very little attention has been given to the impact that commodity price changes have on the South African economy. In South Africa, the role of commodity prices on the economy have been studied by Ocran and Biekpe (2007), Mallick and Sousa (2012), Sujithan et al. (2013) and Chen et al. (2014). Two of these papers, Chen et al. (2014) and Sujithan et al. (2013) arrive at an inconclusive result as of the impact of the commodity prices on South African economy, or give mixed results. Of these three papers, the ones by Mallick and Sousa (2012), Chen et al. (2014), and Sujithan et al. (2013) look of South Africa as a part of a group of countries, while Ocran and Biekpe (2007) studies South Africa alone. This paper also focuses on South Africa in isolation.

Here we focus on four commodity prices and price indices which play a very important role in to South African exports and the economy as a whole. These include the precious metal price index (precmet), the base metal price index (basemet), coal prices (coalp), and the agricultural commodity price index (agricp). The macroeconomic variables include industrial production (indp), the consumer price index (cpi), South African Reserve Bank's repurchase rate (repo), the money supply (M2), and the real effective exchange rate (reer). We focus on three questions: (1) what impact do commodity price changes have on macroeconomic variables in South Africa? (2) Are commodity price shocks alike? (3) How does the South African Reserve Bank respond to such shocks?

This chapter analysis these issues using time series techniques such as cointegration, Vector Error Correction Model, Impulse Response Function (IRF), and Forecast Error Variance Decomposition (FEVD). There are several novel features of this study. First, cointegration among the series in the models is tested. Testing for cointegration among the series ensures that the right model (unrestricted VAR or VECM) is used. This is important as it is explained in section 1.3.3, using unrestricted VAR when there is cointegration relations between the series in the model inference from such model will be incorrect. Second, because South Africa is a major exporter of many commodities, four commodity prices or price indexes are used in this study, to capture the impact of the change of each on the prices on South African economy.

The rest of the chapter is organized as follows. Section 1.2 provides a literature review of earlier work in the area. Section 1.3 offers a discussion of the data and the empirical methodology used. Section 1.4 reports the results while section 1.5 offers a summary of the findings and policy implications.

1.2 Literature Review

The studies that link commodity prices and macroeconomic variables can be grouped into two main categories. First there are those that focus on the impact that commodity prices have on macroeconomic (mainly monetary) variables. Studies that fall into this category are based on the premise that commodity prices contain information that can be used to predict the behavior of macroeconomic variables. In this case, policy makers can use the information contained in the current commodity prices to design policies in order to maintain certain macroeconomic variables at a desired level.

Boughton and Branson (1988) study the value of broad commodity price indexes as predictors of consumer price inflation in the G-7 industrial countries and find that the commodity price index and consumer prices are not co-integrated. Garner (1989), using US monthly data from January 1980 to December 1988 and the Engle-Granger cointegration test, studies the long-run equilibrium relationship between the Commodity Research Bureau (CRB) index, the producer price index for crude material, the gold price, and the consumer price index, and finds no cointegration between any of the commodity prices and the price index. He concludes that using commodity price indices as intermediate targets in monetary policy management will not yield a stable consumer price index over the long run. Using the Johansen cointegration test, Sephton (1991) also finds no long-run equilibrium relationship between commodity price and the consumer price indices. Kugler (1991), using a multivariate cointegration analysis of monthly data for consumer prices in the USA, West Germany, and Japan on a commodity price index, the Dutch Mark, and the Japanese Yen, finds that these six variables move together.

Cody and Mills (1991), using US quarterly data from 1959 to 1987, examine relationships between commodity price indices and monetary policy variables. They conclude that if the policy target of the monetary authorities is short run growth, then the authorities do not need to intervene to increase commodity price indices; however, if the policy target is price stability, then an increase in commodity prices would require using contractionary monetary policy.

Blomberg and Harris (1995), testing eight commonly used indexes, conclude that in the US the predictive power of commodity prices is decreasing in more recent periods. According to them, the decrease in part is due to the diminished role of traditional commodities in U.S. production. Furlong and Ingenito (1996) examine the relationship between changes in non-oil commodity prices and inflation. Their results indicate that the link between commodity prices and inflation has changed dramatically over time. Commodity prices were found to be a robust leading indicators of overall inflation during the 1970s and early 1980s but poor indicators of inflation since the early 1980s. However, when considered in conjunction with other indicators of inflation, non-oil commodity prices have had a more robust relationship with inflation in recent years.

Polley and Lombra (1999) determine the usefulness of commodity prices for conducting monetary policy by examining whether commodity prices, interest rate spreads, and exchange rates can explain incipient errors in the economic forecasts developed by the Federal Reserve's staff and the NBER-ASA panel. Their results suggest that these variables have no additional information beyond which policymakers have already incorporated in their forecasts.

Awokuse and Yang (2003), using Lag Augmented VAR (LA-VAR) model, analyzed the causal relationship between commodity price indices and macroeconomic variables using the US monthly data from 1975 to 2001. They find a unidirectional causality from commodity price indices to both the consumer price index and industrial production index and conclude that commodity prices are important information variables for monetary policy management as signals of future movements in macroeconomic variables.

Bloch et al. (2006), determine the impact of the recent commodity price boom on two commodity exporting countries, Canada and Australia. They find that world commodity prices move pro-cyclically with world industrial production and that rates of change in commodity prices are directly related to domestic inflation in both countries.

Browne and Cronin (2007) use a cointegrating VAR framework and US data to determine the link between commodity prices and consumer prices. They find that long run and short run relationships should exist between commodity prices, consumer prices, and money. They conclude that the influence of commodity prices on consumer prices occurs through a money-driven overshooting of commodity prices being corrected over time.

Hamori (2007), using the Bank of Japan index (BOJ), examines the relationship between the commodity price index and macroeconomic variables in Japan. He finds the BOJ index to be valid leading indicator of the consumer price index before the zero interest policy was introduced, but no such relationship was found after the policy. Medina (2010) finds that, in Latin American countries, fiscal positions generally respond to commodity price shocks. Hassan and Salim (2011) use cointegration and Granger-causality and find that thete is a one way causation from commodity prices to inflation.

Using Vector Error Correction Model (VECM) and GARCH model, Apergis and Papoulakos (2013) study the link between gold prices and Australian Dollars. They find a cointegaration between gold prices and the Australian nominal exchange rate and a flow of volatility from gold prices to the Australian dollar. Bashar and Kabir (2013), using cointegration and Vector Error Correction Model (VECM), find that in the long-run, the Australian dollar is determined by commodity prices, interest rate, and global financial crisis.

More recently, this literature examines the link between commodity prices and monetary policy variables, emphasizing the role that monetary policy has on commodity prices. The premise behind this branch of literature is that global liquidity has often been mentioned as a cause of commodity price surges (Anzuini et al., 2013). Some of the studies that fall in this category include Frankel (1986), Frankel (2008), and Anzuini et al. (2013). Frankel (1986) applies the Dornbusch overshooting model to derive a theoretical no-arbitrage link between oil prices and monetary policy. He shows that low interest rates generate incentives to accumulate inventories and/or postpone extraction. Frankel (2008) finds that low real interest rates lead to high real commodity prices. Anzuini et al. (2013), using a standard VAR model, investigate the empirical relationship between US monetary policy and commodity prices and find that expansionary US monetary policy shocks drive up the broad commodity price index and all of its components.

Some studies have examined the relationship between commodity prices and macroeconomic variables in the context of South Africa. One of these studies, Ocran and Biekpe (2007), uses quarterly data from 1965 to 2004 and time series techniques such as VAR and Granger causality. They find that commodity prices have an information content that can be used for monetary policy purposes. Mallick and Sousa (2012) use quarterly data from 1990 to 2012 and sign restriction VAR and P-VAR to examine the transmission of monetary policy and the impact of fluctuation in commodity prices on real economy in Brazil, Russia, India, China, and South Africa (BRICS). Among other things, they find that, for South Africa, commodity price shocks lead to an appreciation of the real exchange rate but have no effect on output. Sujithan et al. (2013) study the impact of commodity price fluctuations on the economies of the U.S., the Euro area, Brazil, India, Russia and South Africa over the period of 1999 to 2012. They find that, in all counties studied, short-term interest rates respond to commodity price fluctuations and that the linkage between commodity markets and monetary policy instruments is stronger after the recent financial crisis. Chen et al. (2014) analyze the predictive power of commodity prices on inflation in five commodity-exporting countries that have adopted inflation targeting, South Africa, Chile, New Zealand, Canada and Australia. They find that world commodity price aggregates have predictive power for their CPI and PPI inflation, especially when possible structural breaks are included.

The current study contributes to the existing literature by examining the effect of the change in the prices of several commodities on the monetary policy in a resource rich country, South Africa.

1.3 Analytical Framework

1.3.1 Data, Description and Sources

Monthly data include the base metal price index[5] (basemetp), agricultural commodity price index[6] (agricp), precious metal price index[7] (precmetp), and coal prices[8] (coalp). The macroeconomic variables are the industrial production index, the consumer price index (CPI), the money stock (M2), the repurchase interest rate (repo), and the real effective exchange rate (reer). The commodity prices and price indices[9] were retrieved from the World Bank's pink sheet, and the macroeconomic variables were obtained from the IFS-IMF database. The sample period covers from January 1990 to June 2014. With the exception of the repurchase rate, all the series were transformed into natural logarithm. The choice of the commodities used in this study was based on the importance of the class of the commodity on the total exports, the importance of the commodity or commodity group in the country's production, and the availability of data. The coal prices used are the export prices, because domestically consumed coal prices are not available.

[5] The base metal price index is composed of aluminum, copper, iron ore, lead, Nickel, Tin and Zinc.

[6] The agricultural commodity price comprises of food, beverages, and agricultural raw material.

[7] The precious metal price index consists of gold, platinum and silver.

[8] Coal prices are South African Thermal coal prices.

[9] For all price indices (2010=100).

The plots of the series are shown in figure 1.1. Fig. 1.1 shows that since early 2000s commodity prices have surged upwards and became more fluctuating.

1.3.2 Unit Root Test

Most macroeconomic data are non-stationary. Hence, it is customary in macroeconomic research to pretest the variables for unit root and transform the variables to ensure that the variables are stationary. If the variables in the regression model are not stationary, then the standard assumptions for asymptotic analysis will not be valid. This means that the usual "t-ratios" will not follow a t-distribution, so we cannot validly undertake hypothesis tests about the regression parameters, and the persistence of shocks will be infinite. If a series is non-stationary, then it must be differenced d times before it becomes stationary; at that point, it is said to be integrated of order d. The most common unit root test is the Augmented Dickey Fuller (ADF)[10] test. The ADF test can be illustrated by considering equation 1.1.

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \varphi_1 \Delta y_{t-1} + \ldots + \varphi_{p-1} \Delta y_{t-p+1} + \epsilon_t \qquad (1.1)$$

where $\epsilon_t \sim iid(0, \sigma_\epsilon^2)$

The null hypothesis for ADF is that $\gamma = 0$, against the alternative hypothesis that $\gamma < 0$. When the null hypothesis is true, then the series has a unit root or is non-stationary, otherwise the series is stationary. An important practical issue in implementing the ADF test is the specification of the optimal number of lags, p, to be used. In this study the optimal lag length is determined by minimizing the Akaike Information Criteria[11] (AIC). The use of AIC is preferred to SIC, despite the fact that the latter chooses a more parsimonious model. AIC is preferred to ensure that the residuals from the model satisfy the model diagnostic test[12], such as the Portmanteau LB test and the ARCH-LM test. Moreover, because the sample size used in this study is considerably large, the loss of data due to the use of AIC will have a negligible effect on the unit root test results.

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[10] For more details see Dickey and Fuller (1979).

[11] $AIC = -2lnL + 2k$, where L is the maximum likelihood and k is the number of parameters.

[12] For a more detailed discussion of the diagnostic tests refer to section 1.3.5.

The other unit root test that is also commonly used in the literature is the Philips-Perron (PP)[13] test. The PP test offers an alternative to the ADF test for correcting for serial correlation and heteroskedasticity in the residuals. The PP test can be illustrated in the following equation:

$$\Delta y_t = \beta' D_t + \pi y_{t-1} + \varepsilon_t \tag{1.2}$$

where D_t contains deterministic trends, and ε_t are I(0) residuals and may be heteroskedastic. The null hypothesis, $\pi = 0$, is that the series has unit root; the alternative, $\pi < 0$, is that the series is stationary. The test statistic of the PP test has the same distribution as the Dickey–Fuller statistics. However, the PP test statistic is robust to serial correlation and heteroskedasticity in the residuals by using the Newey–West (1987) heteroskedasticity and an autocorrelation-consistent covariance matrix estimator.

1.3.3 Cointegration

Cointegration analysis is concerned with estimating long run economic relationships among non-stationary, integrated variables. The most widely used cointegration method, and the one used in this study, is the Johansen and Joselius cointegration[14] procedure. This procedure uses two tests, the Trace test and the Maximum Eigenvalue test, to determine the number of cointegrating vectors, based on the characteristic roots. For both tests, the null hypothesis is that there are, at most, r cointegrating vectors: The trace test, given by equation 1.3 has an alternative hypothesis of, at most, k cointegrating vectors. The Maximum Eigenvalue Test, given in equation 1.4, has an alternative hypothesis that there are, at most, r+1 cointegrating vectors. For both tests r = 0, 1, 2, …, k-1, and T is the sample size.

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{k} \ln(1-\hat{\lambda}_i) \tag{1.3}$$

$$\lambda_{\max}(r, r+1) = -T\ln(1-\hat{\lambda}_{r+1}) \tag{1.4}$$

[13] For more details about the Phillips and Perron test refer to Phillips and Perron (1988).

[14] For more details refer to Johansen and Joselius (1990).

Cointegration analysis is important because if two or more series are non-stationary and cointegrated, then a Vector Autoregressive (VAR) model is misspecified since there is a long-run co-movement between the series. In this case, the VAR model needs to include an error correction term, hence the model is known as Vector Error Correction (VEC) model[15].

1.3.4 Vector Autoregressive and Vector Error Correction Models

To investigate the dynamic effects of commodity price shocks on the economy, a Vector Autoregressive (VAR) model is used. The VAR model, initially introduced by Sims (1980), is a dynamic system of linear equations in which the variables on the left hand side are a function of its lags and lags of the other variables. For a set of n time series variables, a structural form VAR model of order p, (VAR (p)), can be represented by equation 1.5.

$$A_0X_t = \theta + A_1X_{t-1} + A_2X_{t-2} + \ldots + A_pX_{t-p} + u_t \tag{1.5}$$

where X_t is a vector of endogenous variable, θ is a column vector of constants. Ai is a (nxn) coefficient matrices capturing the dynamic interactions between the variables in the model; p is the number of lags; and $u_t = (u_{1t}, u_{2t}, \ldots, u_{nt})'$ is an n-dimensional matrix of unobservable, white noise, structural disturbances with a positive definite covariance matrix $E(uu') = \Sigma u$. The reduced form of X_t can be expressed as:

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \ldots + \alpha_p X_{t-p} + \varepsilon_t \tag{1.6}$$

where $\alpha_i = A_0^{-1}A_i$, and $\varepsilon_t = A_0^{-1}u_t$ is a white noise process with an invertible and symmetric covariance matrix Ω. The challenge with using the reduced model, given in equation 1.5, is that there is not a one to one mapping of parameters from (1.5) to (1.6), hence one is unable to derive the true values of parameters of A_i's. The literature has proposed a number of different ways of uncovering the parameters in the structural form equation from the reduced form. One procedure that is commonly used in the literature, which is also adopted in this study, is the Cholesky

[15] For more detail about VECM see Engle and Granger (1987).

Decomposition[16], suggested by Sims (1980). The Cholesky decomposition is a recursive identification restriction technique, which assumes that the covariance matrix, Σ, is diagonal, and matrix, A_0, is a lower triangular matrix, thereby imposing n*(n-1)/2 extra restrictions and ensuring the identification of the structural model. In this study four[17] different, six-variable VAR models are estimated using the following Cholesky ordering $X_t = [comp, indp, cpi, M2, repo, reer]$.
where comp is commodity price, indp is the industrial production, cpi is the consumer price index, M2 is the money stock, repo is the reserve bank's repurchase rate, and reer is the effective real exchange rate.
This ordering implies that in matrix form, the relation between the reduced-form errors and the structural disturbances can be expressed as in equation 1.7.

The choice of this recursive ordering is justified in the following terms. Commodity prices being determined in international markets are the least endogenous variables, hence the assumption that none of the shocks to other variables has a contemporaneous impact on commodity prices. Next, the industrial production index is based on the assumption that real activity does not contemporaneously respond to the shock in the other endogenous variables in the model, since nominal variables do not have an immediate impact on the real variable.

$$\begin{bmatrix} u_t^{comp} \\ u_t^{indp} \\ u_t^{cpi} \\ u_t^{M2} \\ u_t^{repo} \\ u_t^{reer} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \theta_{2,1} & 1 & 0 & 0 & 0 & 0 \\ \theta_{3,1} & \theta_{3,2} & 1 & 0 & 0 & 0 \\ \theta_{4,1} & \theta_{4,2} & \theta_{4,3} & 1 & 0 & 0 \\ \theta_{5,1} & \theta_{5,2} & \theta_{5,3} & \theta_{5,4} & 1 & 0 \\ \theta_{6,1} & \theta_{6,2} & \theta_{6,3} & \theta_{6,4} & \theta_{6,5} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^{comp} \\ \varepsilon_t^{indp} \\ \varepsilon_t^{cpi} \\ \varepsilon_t^{M2} \\ \varepsilon_t^{repo} \\ \varepsilon_t^{reer} \end{bmatrix} \tag{1.7}$$

Money Supply is ordered next. Since it is a policy variable, it does not contemporaneously respond to inflation, interest rates, and exchange rate, but it does respond immediately to shocks in real activities and the commodity prices.

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[16] For identification methods see Sims (1986) and Blanchard and Quah (1989).

[17] An alternative would be to estimate a nine-variable VAR model that includes the four commodity prices and the Monetary Policy variables in equation 1.6. For more details about this see Kilian (2009).

Inflation is ordered next. It is assumed that inflation responds contemporaneously to exogenous shocks in commodity prices, industrial production, and money supply, but does not respond contemporaneously to shocks in interest rates and exchange rate. It is also assumed that interest rates do not respond contemporaneously to current account shocks, exchange rates, but it is contemporaneously responsive to the other endogenous variables in the model.

Finally, exchange rate comes last in the order to indicate that all variables in the model have a contemporaneous impact on the exchange rate, but it has no contemporaneous impact on any other variable in the model. This assumption is plausible taking into account that South Africa has a flexible exchange rate system and uses an inflation targeting system.

Given the existence of at least one cointegration relation among the series that are to be used in the model, the VEC model can be expressed as,

$$\Delta X_t = \Pi X_{t-1} + \Gamma_1 \Delta X_{t-1} + \ . \ . \ . + \Gamma_{p-1} \Delta X_{t-p+1} + u_t \tag{1.8}$$

where

$\Pi = \alpha\beta = -\left(I_k - A_1 - \ . \ . \ . - A_p\right)$ and $\Gamma_j = -\left(A_{j+1} + \ . \ . \ . + A_p\right)$ for $j = 1, \ . \ . \ . , p - 1$.

Δ is the first difference operator, X_t is the vector of endogenous variables, Γ_j are the short run-run dynamic coefficient matrix, α and β are (pxr) and (rxp) full rank matrices of loading factors and long-coefficients, respectively, and u_t is a vector of white process.

The main applied tool in the VAR/VECM model estimation is the impulse response function (IRF) and Variance Decomposition (VDC). After the model is correctly identified, the dynamic response of macroeconomic variables to innovation in commodity prices can be examined through the Impulse Response Function. According to Sims (1980), the Impulse Response Function allows one to trace out the time path of the various shocks on the variables included in the VAR model. The VDC, on the other hand, shows the proportion of variation in a particular variable that is due to its own variation and the variation of other variables. For a more detailed description of IRF and VDC refer to section 2.3.6.

1.3.5 Model Diagnostics

To determine the adequacy of a VAR or VEC models, there are several procedures available to ensure that the chosen model represents the data generating process adequately. The most widely used procedure considers the residuals from the estimated model and tests them to determine if they meet the white noise assumption. The tests include: the Portmanteau LB test, the LM test for ARCH effects, and the Jarque-Bera for Normality test.

The Portmanteau LB test checks the autocorrelation of the model residuals up to the chosen lag. The null hypothesis is $H_0: E(u_t u'_{t-i}) = 0, \quad i = 1, \ . \ . \ . \ , h,$

Against the alternative that at least one covariance e and, hence, one autocorrelation is nonzero. The test statistic has the form

$$Q_h^* = T^2 \sum_{j=1}^{h} \frac{1}{T-j} tr\left[\hat{C}_j \hat{C}_0^{-1} \hat{C}_j' \hat{C}_0^{-1}\right] \tag{1.9}$$

Where $\hat{C}_j = T^{-1} \sum_{t=j+1}^{T} \hat{\epsilon}_t \hat{\epsilon}'_{t-j}$

If the $\hat{u}_t$ are residuals from a stable VAR (p) process, Q_h has an approximate $\chi^2(K^2h - n^*)$, where n^* is the number of estimated VAR parameters.

The LM test for the ARCH effects in the residuals checks whether the residuals are homokedastic. The ARCH-LM test may be based on the multivariate regression model

$vech(\hat{u}_t \hat{u}'_t) = \beta_0 + \beta_1 vech\left(\hat{u}_{t-1} \widehat{u'}_{t-1}\right) + \ . \ . \ . + \beta_q vech(\hat{u}_{t-q} \widehat{u'}_{t-q} + \epsilon_t$

where vech is the column stacking operator for symmetric matrices which stacks the columns from the main diagonal downwards, β_0 has a dimension of $\frac{1}{2} K(K+1)$ and the β_j are coefficient matrices with $(\frac{1}{2}K(K+1) \text{ X } \frac{1}{2}K(K+1))$, and $j = 1, \ . \ . \ . \ , q$. The null hypothesis is $H_0: \beta_1 = . \ . \ . = \beta_q$ against the alternative $H_1: \beta_1 \neq 0 \ or \ . \ . \ . \ \beta_q \neq 0$.

The Test statistic is $LM(q) = \frac{1}{2}TK(K+1)R_m^2$, where $R_m^2 = 1 - \frac{2}{K(K+1)} tr(\widehat{\Omega}\widehat{\Omega}_0^{-1})$, and $\widehat{\Omega}$ is the residual covariance matrix with a dimension of $\frac{1}{2}K(K+1)$.

The Jarque-Berra test checks if the residuals of the estimated model are normally distributed. The null hypothesis is that the residuals are normally distributed, skewness is zero and excess kurtosis is zero; and the alternative hypothesis is that the residuals aren't normally distributed. The Jarque-Bera test statistic is: $JB = n * \left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right]$, where K is the Kurtosis, and S^2 is the sample variance.

1.4 Analysis of Results

1.4.1 Unit Root Test

The results of the Augmented Dickey-Fuller (ADF) test are reported in Table 1.1. In order to select the lag length, p, using the correct specification of the model, constant or constant and trend, we start with a maximum lag of 12 and keep reducing them by one. The number of lags that minimizes the Akaike Information Criterion (AIC) is selected. The optimal lag lengths for the series in levels vary from 7 lags for M2, to 1 lags for the cpi, basemetp and coalp. Whereas the optimal lags for the series in first difference vary from 3 lags for reer to 1 lag for the majority of the series. The first row indicates that we fail to reject the null hypothesis that base metal prices (basemetp) have unit root since the absolute value of the test statistic, -1.22, is smaller than the absolute value of the critical value[18] , -2.86. The results also indicate that, when differenced, basemetp becomes stationary, since the absolute value of the test statistics, -11.38, is greater than the absolute value of the critical value, -1.95. The results of the rest of the series indicate that we fail to reject the null hypothesis of non-stationarity when the series are in levels, but the null hypothesis is rejected when the series are differenced. Hence we can conclude that all the series in levels have unit root but become stationary when they are differenced. The results of the Phillips-Perron test (table 1.2) also indicate that when the series are in levels we fail to reject the null hypothesis that the series have unit root. However, when differenced once, we reject the null hypothesis that the series have unit root. These results also imply that all the series are integrated of order one, I(1).

Since these results show that all the series are integrated of the same order, I(1), it is appropriate to use the Johansen cointegtaion test to determine the number of cointegration relationships in the VAR models under consideration.

1.4.2 Cointegration Test Results

The results of the cointegration test are displayed in Table 1.3. The results for both trace and maximum Eigen value tests reveal the existence of at least one cointegration relation among the variables included in all four models estimated. The existence of a cointegration relations in

[18] The critical values are drawn from Davidson, R. and MacKinnon, J. (1993),"Estimation and Inference in Econometrics" p 708, table 20.1, Oxford University Press, London.

these models means that, although the series are non-stationary individually, there exist two linear combinations among these series that are stationary. This means that there is a long-run equilibrium relationship among the series. Moreover, existence of cointegration among the variables also indicates that there is no possibility of spurious relationships among the series in the model. As stated earlier, the existence of cointegration in these models implies that the VAR models needs to include an error correction term, transforming the model into a VECM. The inclusion of the error correction term is to ensure a correction of what would be a misspecified model that would render inferences, such as Impulse Response Functions, Granger-causality tests and Variance Error Decomposition, misleading (Granger, 1988).

1.4.3 Impulse Response Function Results

Given the existence of the long-run relationship, established in the previous section, the next step is the identification and estimation of the correct VECM, which will be used to examine the dynamic impact of the commodity prices on the macroeconomic variables using the IRF and FEVD. The specifications of the estimated VECM are given in table 1.4. All models have a constant and deterministic trend and use one cointegrating vector[19].

Once the correct VECM has been estimated the next step is to carry out the IRF analysis. The IRFs trace the variation of the macroeconomic variables over time to a one standard deviation shock of the commodity prices under consideration. The results of the impulse response functions and their corresponding confidence bands are displayed in figures 1.2, 1.3, 1.4, and 1.5 for models 1A, 1B, 1C and 1D, respectively. Confidence intervals at the 95% level are computed for the impulse responses using bootstrap methods. We follow the standard percentile interval method as described in Breitung et al. (2004) with 1000 bootstrap residuals.

The results indicate that for most commodities, a positive shock to any of the commodity prices is followed by an increase in real activity. These results are agree with expectations, taking into account that South Africa is a major exporter of these commodities, since higher prices would be seen as an incentive to increase production, leading to higher economic activity. A positive shock to base metal prices has an immediate increase in real activity, and the increase continues for the next four months before slowly decreasing. However, for the entire time period studied, the

[19] The number of cointegration vectors were taken from the maximum eigen value results.

level of economic activity is higher than the initial value before the shock. This finding contradicts the finding by Mallick and Sousa (2012), who find no commodity price impact on South African output. A possible explanation for the different results could be that in their studies, the commodity price index was heavily influenced by oil prices, which is a commodity that South Africa imports. However, in the current study, all the commodities are part of South Africa's main exports.

Figure 1.2 shows that a positive shock in base metal prices causes an increase in economic real activity which starts causing inflationary pressure and the reserve bank responds by increasing the repurchase rate as a way of containing the inflationary pressures. In figure 1.3, the positive shock in precious metal prices has a very small and brief effect on economic real activity which fades immediately. After about eight months, the level of output is less than the original value before the shock. The shock also has an immediate but small inflationary pressure, which is also followed by an increase in the interest rates by the monetary authorities as a way of easing the inflationary pressure.

Figure 1.4 shows that a positive shock in agricultural commodity prices has an initial positive effect on the industrial production, but after about 16 months the effect on the industrial production fades away and becomes negative. Similarly, positive shock in agricultural commodity prices creates inflationary pressures. As a response, the Reserve Bank increases the interest rates slightly as a way of easing the inflationary pressure to keep the inflation rate within the targeted range of 3 to 6 percent.

The IRF results in figure 1.5 show that a positive shock in coal prices has a negative effect on the production level, but an insignificant effect on the price level. As it was explained earlier coal is the main source of electricity used in South Africa, hence other things equal, higher coal prices increase the coast of production, which in turn has a negative effect on the level of production. However, the increase in coal prices tend to have an insignificant effect on the consumer price level, in part due to the way the CPI is computed, which does not include coal prices directly. The negative effect that the increase in coal prices has on the production level, are followed by an expansionary monetary policy reflected in the reduction in the repurchase rate in order to increase the level of economic activity.

So, overall, the results from the IRF indicate that shock to prices if different commodities produces different output and inflationary outcomes, which in turn yields to different monetary policy actions by the monetary authorities.

1.4.4 *Forecast Error Variance Decomposition*

As previously explained, the forecast error variance decomposition shows the proportion of forecast error accounted for by the variables in the model at different time horizons. The variance decomposition results (tables 1.6 to 1.9) are consistent with the findings of the impulse response functions. For all models, variations in the commodity prices are largely accounted for by variations in the commodity prices themselves. In the first month, 100% of the variations in the commodity prices are accounted for by their own variations. After 36 months, the variation of the commodity prices is still largely accounted for by their own variations. The results in table 1.6 indicate that after 36 months about 76% of the variation in the base metal prices in model 1A is explained by its own variation; 52 % of the variation in the precious metal prices is explained by its own variation in model 1B; about 93 % of the variation in the agricultural prices is explained by its own variability in model 1C; and 68 % of the variations of coal prices are explained by its own variation in model 1D. These results are to some extent reinforcing that commodity variables are exogenous in the system, which validates the position of the commodity prices in the Cholesky decomposition.

The results in table 1.6 also show that a positive shock in base metal prices (basemetp) has no immediate impact on the production level, but explains about 28% of the variation in the industrial production by the end of 36 months. Also, as the IRF indicated, the shock in base metal prices has little effect on the inflation level. In this case the results in table 1.5 show that variations in base metal prices account for about 0% variations in the price levels in the first month, and about 2.5% at the end of 36 months. The increase in economic activity caused by the increase in base metal prices causes the monetary authority implement a contractionary policy by increasing the interest rates (repo) as a measure of preventing the economy from overheating. As a result of the actions by the monetary authorities, variations in base metal prices that account for 0% in the changes in repurchase rate in the first month, account about 22.7% variation in the interest rates after 36 months.

The results in table 1.7 also are consistent with respective IRF results presented in figure 1.3. A positive shock in precious metal prices account for very little variations in real economic activity. In this case, the highest variation of the industrial production that is accounted for by precious metal prices at any period is less than 2%. A Possible explanation for this rather low contribution of precious metal price variability to changes in industrial production could be the fact that a large portion of the precious metal exports in South Africa have a low value added (Davis, G, A., 2010). Similarly, the variations in precious metal prices also accounts for very little variations in consumer price index. Only about 0.05% and 1.8% of the variation in CPI is explained by changes in precious metal prices in the first month and third year, respectively. As a result of the low impact of the variations of precious metal prices on both industrial production and consumer price index the variation of repurchase rate that is attributed to variation in precious metal prices is very small. Throughout the entire period of the study highest variation in the repurchase rate that is explained by variations in the precious metal prices is less than 1%.

Table 1.8 shows the results of the FEVD for model 1C. The results indicate that agricultural commodity prices account for 0% changes in industrial production in the first month and about 18.9% variations after three years. Similarly, changes in the agricultural commodity prices explain about 0.0% and 6.02% variations in consumer prices in the first month and third year, respectively. The effects of the agricultural commodity on industrial production are also reflected by the action by the Reserve Bank in response to such shock. In the first month after the shock, about 0.06% of variations in the interest rates are explained by changes in the variations in agricultural commodity prices, and by the end of the third year, about 14.6% variations in the interest rates are accounted for by changes in agricultural commodity prices.

The results in table 1.9 show that variations in coal prices do explain changes in industrial production. Although the variation of industrial production that is accounted for by changes in coal prices is about 1% in the first month, by the end of the end of the third year, about 21.8% of the variation in industrial production is explained by the changes in the coal prices. This rather large impact of the change in coal prices on change in industrial production is to be expected as mentioned earlier, coal accounts for more than 70% of the energy used in South Africa. The results in table 1.9 also show that if compared to other commodity price shocks, shocks to coal prices captured in model 1D, have the least impact on the variation of the CPI. The highest variation of CPI due to change in coal price is only 0.39% in the 24th month. Two possible explanations can be advanced for this rather low explanation of variation in CPI due to commodity prices. First, South Africa has an inflation targeting policy. As long as the monetary authorities are successful in meeting the target, then the increase in commodity prices should have a small effect on the consumer price level. Another possible reason could be the way the CPI is computed; it does not include most of the commodities under consideration in this study. The fact that shocks to agricultural commodity prices, in model 1C, have the largest impact on the CPI is an indication of the plausibility of the second reason. Agricultural commodities are more likely to be part of the CPI than any other commodities analyzed. This large impact of changes in coal prices on inflationary pressure is also reflected in the Reserve Bank's actions. Variations in coal prices account for about 10.9% of the changes in the Reserve Banks's repurchase rate.

Finally, the results also indicate that changes in the prices of different commodities yield different impacts on the real effective exchange rate. With exception of shocks to coal prices, which account about 10.2% of variation in real effective exchange rate, shocks to the price of other commodities have a rather small impact on the effective exchange rate.

So, the results from the FEVD discussed in this section corroborate the IRF discussed in the previous section. Shocks to different commodity prices tend to have different effects on the monetary policy variables, hence requiring different policy actions from the monetary authorities.

1.4.5 Model Diagnostics

In order to determine the suitability of the models used, diagnostic tests were carried out. The diagnostic tests consists of testing the model residuals to find out if they conform to common assumptions. The results of the diagnostic test are summarized in table 1.5. The results indicate in all four models there are no violations of homokedasticity and serial correlation assumptions, since all the p-values are greater than 5%. The results however, do show a violation of the normality assumption for all the models, since the p-value for the Jarque-Berra test is equal to zero in all four models. However, according to Paruolo (1997), non-normality as a result of excess kurtosis does not affect the results.

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1.5 Conclusion

This chapter analyzes the link between commodity prices and monetary policy in South Africa. More specifically, it tries to answer the following two questions: (1) What is the impact on the South African macroeconomy of commodity prices changes? (2) Are commodity price shocks similar? (3) How does the central bank of South Africa respond to such changes in the commodity prices? To answer these questions, this chapter focuses on the commodities for which South Africa is a major producer, namely, coal, base metals, precious metals, and agricultural commodities. Monthly data from January 1990 to June 2014 is used to study the impact of the increase in these commodity prices on industrial production, price level, real exchange rate, interest rate (repo rate), and money supply (M2) using time series methodology like VAR, VECM, and Impulse Response functions.

The results indicate that changes in the prices of different commodities lead to different effects on the macroeconomic variables studied. Although in many cases the effects are not statistically significant, the signs of the impulses do provide useful information about the direction of the effects. We interpret these directions as being useful to policymakers.

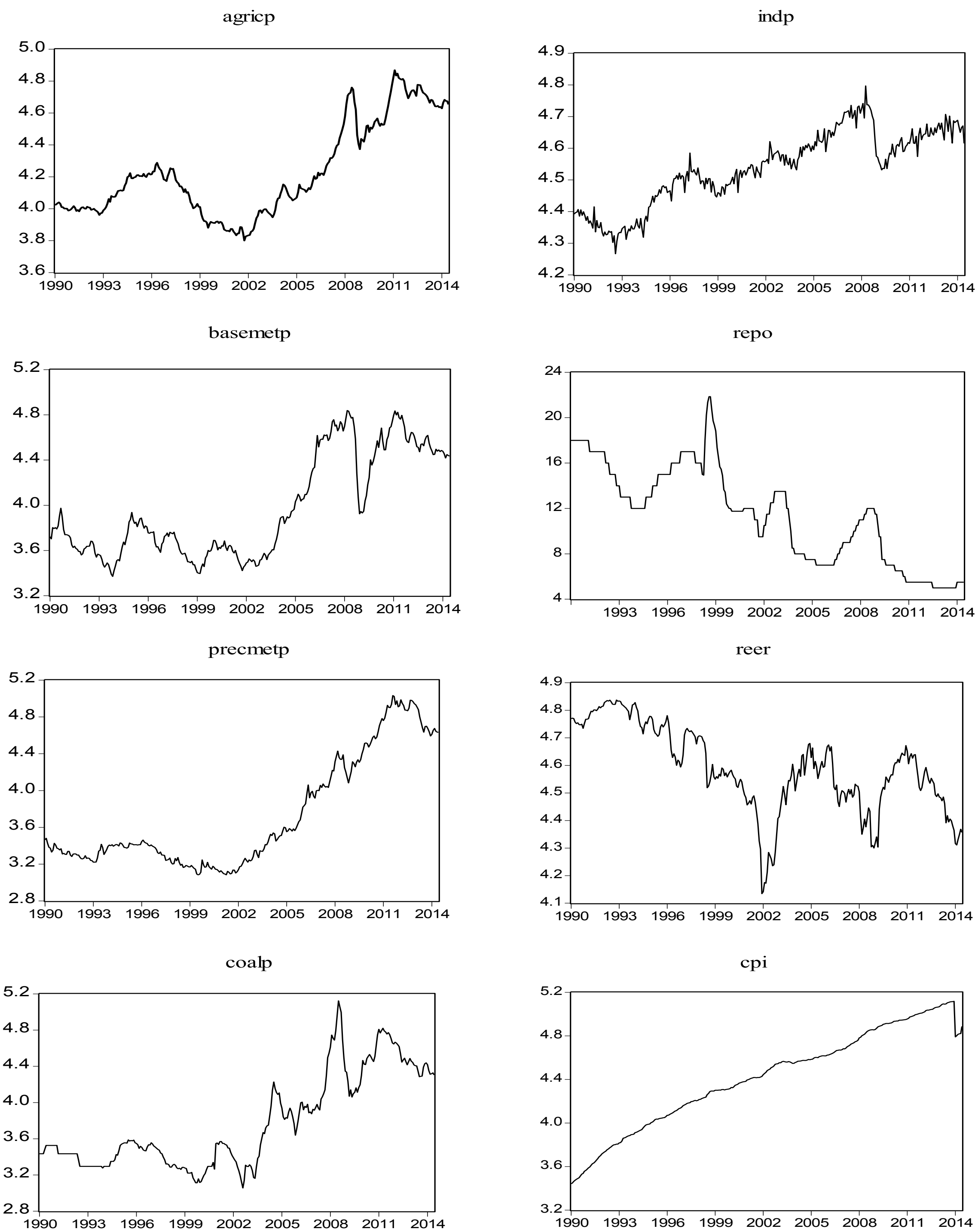
With the exception of coal prices, a positive shock to all other commodity prices leads to an increase in real economic activity. Shocks to coal prices have a negative and statistically significant effect on industrial production; however, the effect is only significant after about one year. Shocks to base metal prices have the largest impact on industrial production, and the effect is statistically significant. A shock to agricultural commodity prices has a positive effect on industrial production, and the effect is significant for about eight months. Shocks to the precious metal price have an insignificant impact on industrial production

Similar to the effect on industrial production, the results indicate that shocks to the prices of the different commodities tend to have different effects on the price level. With the exception of coal prices, a positive shock to all other commodity prices leads to a positive effect on the price level. Only a shock to agricultural commodity prices has a statistically significant effect on the prices, and the effect becomes significant only after 16 months. One possible reason why only agricultural commodity prices have a significant effect on the price level has to do with the way the consumer price index is computed. Most of the commodities considered in this study, such as metals and coal, are not included in the computation of CPI.

Commodity prices are also found to have an impact on the real value of the South African currency. Shocks to coal prices have an immediate real appreciation in the real exchange rates, while shocks to base metals and agricultural commodity prices have a small, increasing appreciation in the real exchange rate that begins to depreciate after about three months. However, none of the shocks have a statistically significant effect on the real exchange rate.

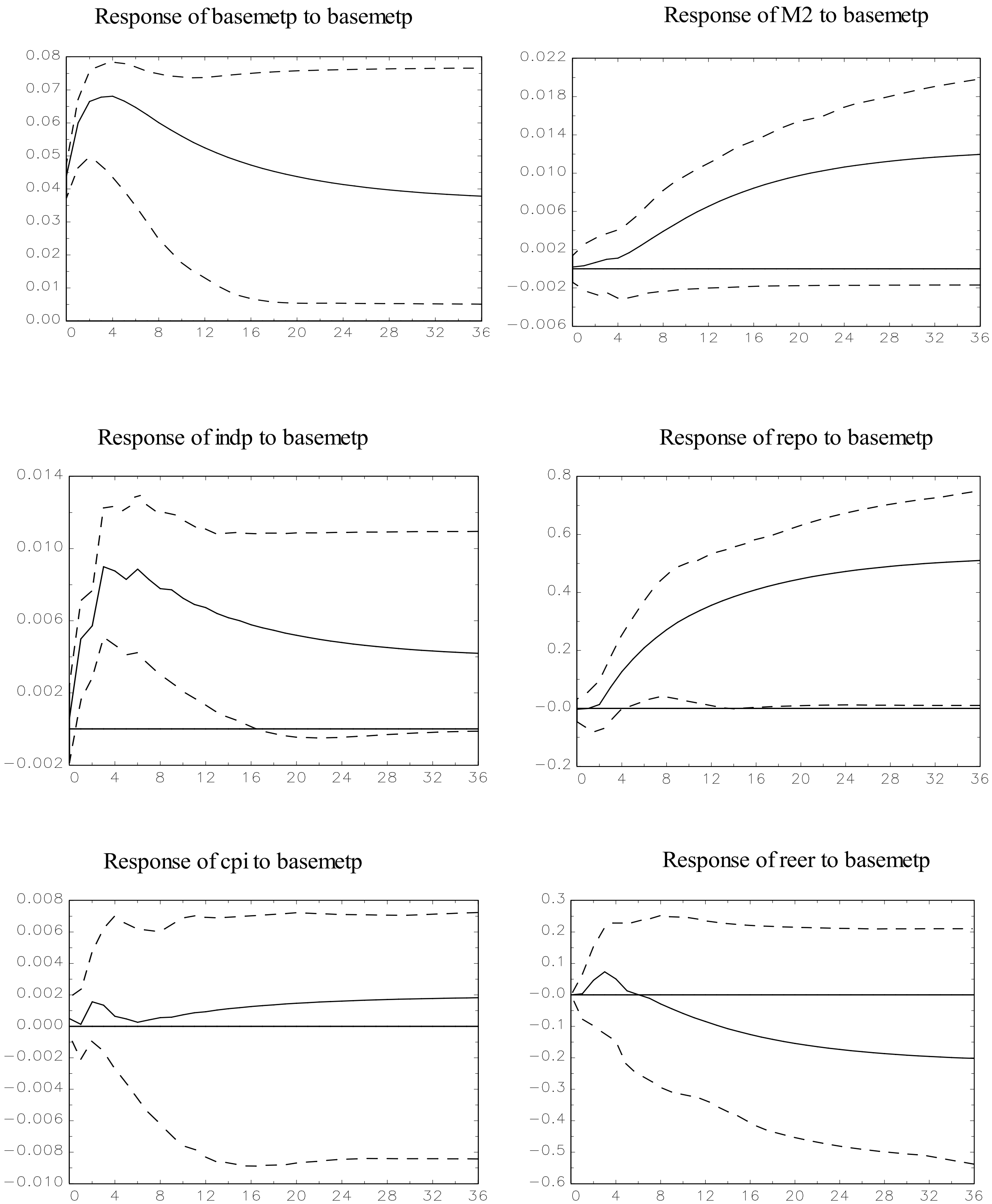
These findings have a very important implication on the monetary policy in South Africa. Contrary to some previous studies that advocate a one size fits all monetary policy in the face of an increase in commodity price, this study has shown that changes to the prices of different commodities have different macroeconomic impacts. Thus, any consideration of monetary policy response to commodity price increase should be specific depending on the type of commodity price that is changing. This implies that a “one size fits all” monetary policy in response to fluctuations in commodity prices might not be the right approach. Moreover, among the commodities under consideration, only changes in agricultural commodities and coal prices, which have a positive and statistically significant effect on the price level, would offer more important inputs in the monetary policy formulation, given that the South African Reserve Bank uses an inflation targeting monetary policy framework. Finally, given the lag difference in the effects that different commodity prices have on monetary variables, monetary authorities need to take this into account should they decide to design a monetary policy response to commodity price changes.

Figure 1.1 Line Plots of Natural Logarithms of the Series



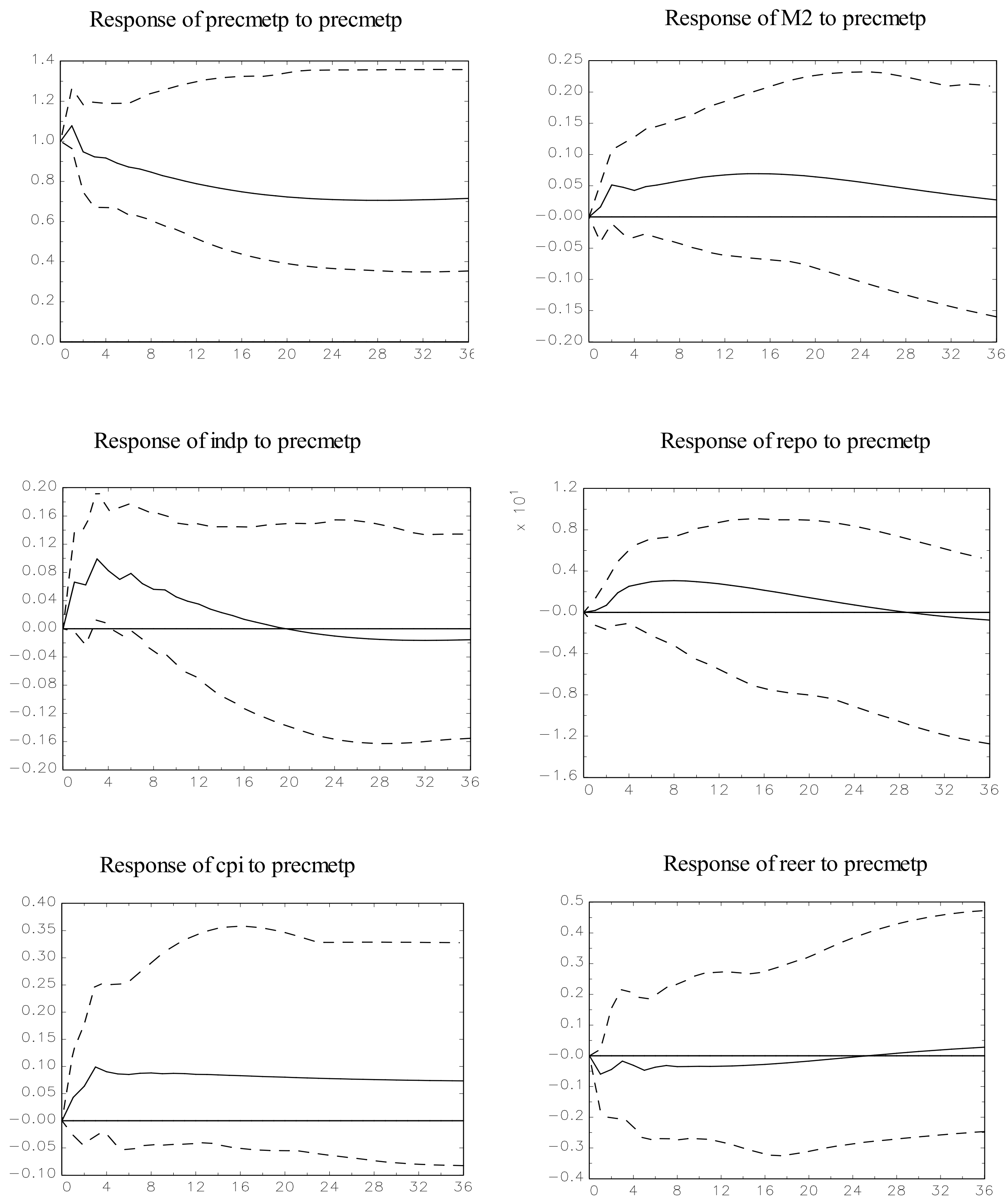
Notes: agricp is the agricultural commodity prices, basemetp is the base metal price index, precmetp is the precious metals price index, coalp is the coal price, indp is the industrial production, cpi is the consumer price index, repo is the reserve bank's repurchase rate, and reer is the real effective exchange rate.

Figure 1.2 Impulse Response to a shock in base metal prices (basemetp)



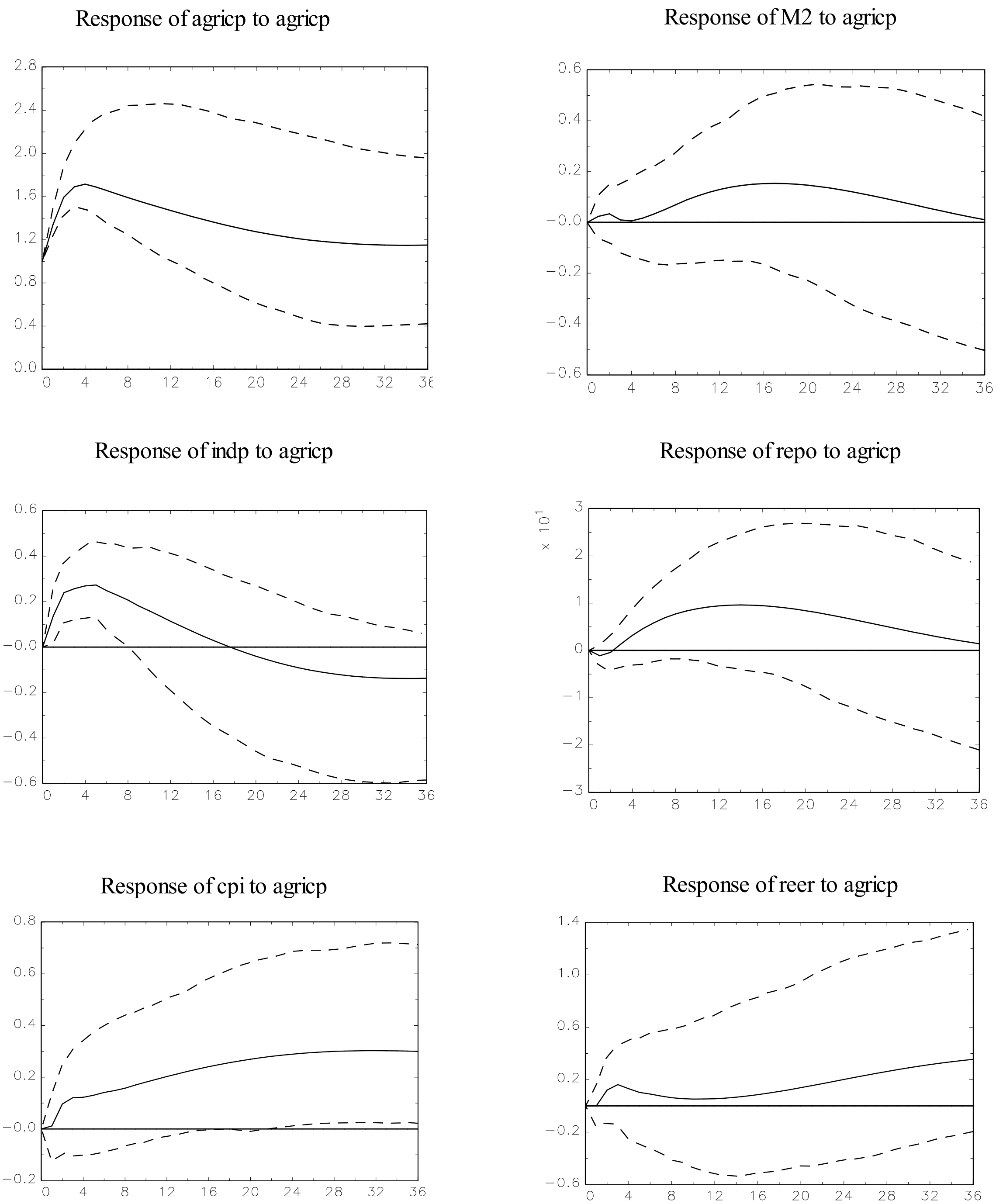
Notes: Cholesky order (basemet, indp, cpi, M2, repo, reer). Indp is the industrial production, cpi is the consumer price index, M2 is the money stock, repo is the reserve bank's repurchase rate, and reer is the real effective exchange rate. The vertical axis represents the value of the response variable and the horizontal axis represents the number of periods.

Figure 1.3 Impulse Response Functions to a shock in precious metal prices (precmetp)



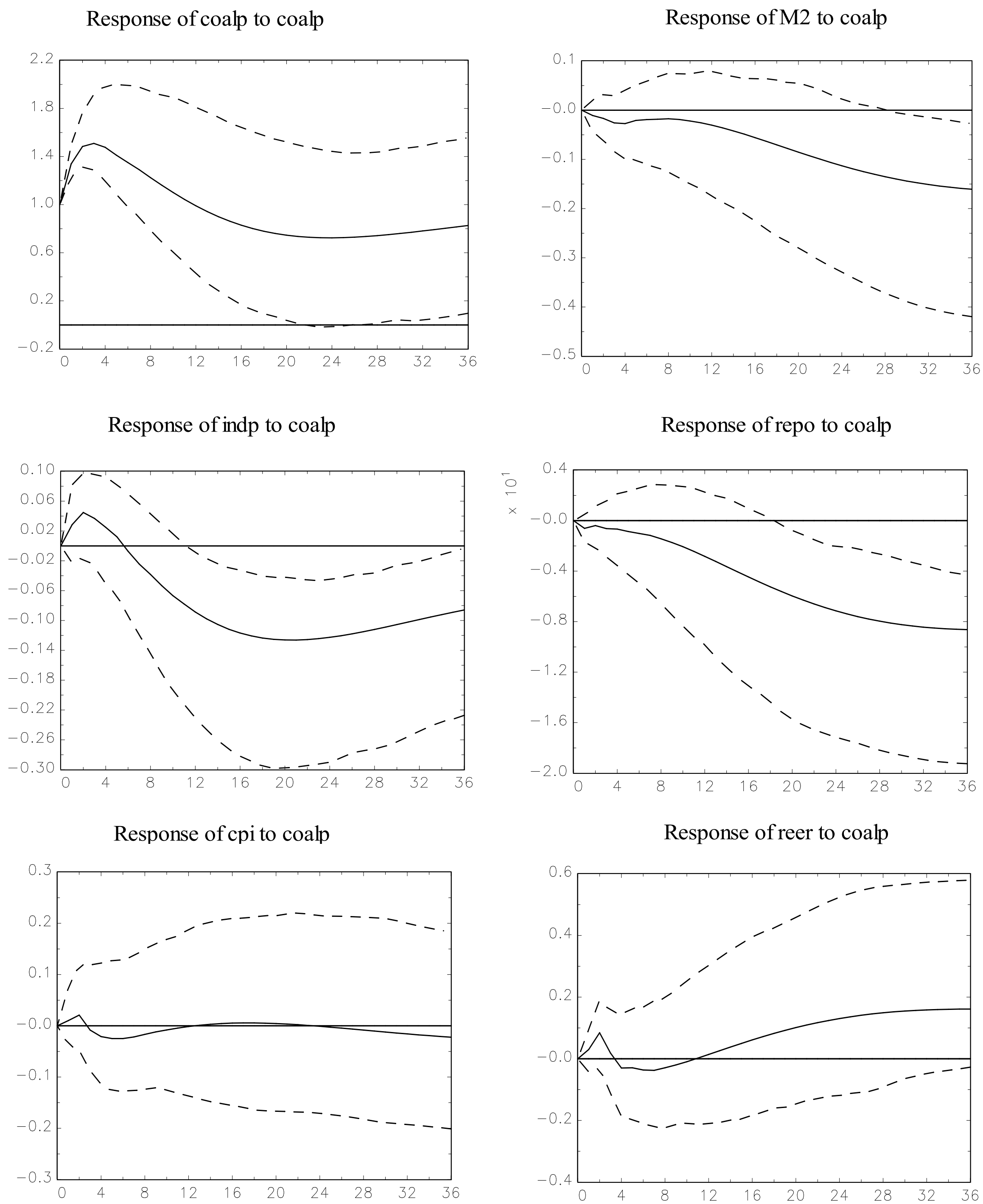
Notes: Cholesky order (precmetp, indp, cpi, M2, repo, reer). indp is the industrial production, cpi is the consumer price index, M2 is the money stock, repo is the reserve bank's repurchase rate, and reer is the real effective exchange rate. The vertical axis represents the value of the response variable and the horizontal axis represents the number of periods.

Figure 1.4 Impulse Response Function to a shock of agricultural commodity prices (agricp)



Notes: Cholesky order (agricp, indp, cpi, M2, repo, reer). indp is the industrial production, cpi is the consumer price index, M2 is the money stock, repo is the reserve bank's repurchase rate, and reer is the real effective exchange rate. The vertical axis represents the value of the response variable and the horizontal axis represents the number of periods.

Figure 1.5 Impulse Response Functions to a shock in coal prices



Notes: Cholesky order (coalp, indp, cpi, M2, repo, reer). indp is the industrial production, cpi is the consumer price index, M2 is the money stock, repo is the reserve bank's repurchase rate, and reer is the real effective exchange rate. The vertical axis represents the value of the response variable and the horizontal axis represents the number of periods.

Table 1.1 Unit Root Test - Augmented Dickey-Fuller Test

	Levels			First Difference		
Variable	Model	Lags	Test Stat.	Model	Lags	Test Stat.
basemetp	c	1	-1.22	none	1	-11.38*
agricp	c,t	2	-1.92	none	1	-8.26*
precmetp	c,t	2	-1.71	none	1	-14.72*
coalp	c,t	1	-2.64	none	1	-11.28*
indp	c,t	3	-2.3	none	2	-10.58*
cpi	c,t	1	-1.57	c	1	-16.58*
repo	c	3	-1.78	none	2	-6.65*
M2	c,t	7	-1.04	c	2	-6.70*
reer	c	6	-1.86	none	3	-5.47*

Notes: "*" indicates rejection of the null hypothesis. The critical values for ADF test for 1%, 5% and 10% significance levels for model with "c" are -3.43, -2.86, and -2.57; for model with "c,t" are -3.96,-3.41, and -3.13; and for a model with no deterministic trend are -2.56, -1.93, -1.61. Number of lags was selected by minimizing the AIC.

Table 1.2 Unit Root Test - Philip Peron (PP) Test

	Levels		First Difference	
Variable	Model	Test Stat.	Model	Test Stat.
basemetp	c	-1.18	none	-11.50*
agricp	c,t	-1.65	none	-11.32*
precmetp	c,t	-1.82	none	-14.73*
coalp	c,t	-2.48	none	-11.35*
indp	c,t	-3.14	none	-27.73*
cpi	c,t	-1.57	c	-16.58*
repo	c	-1.41	none	-12.92*
M2	c,t	-0.41	c	-18.54*
reer	c	-1.8	none	-14.30*

Notes: "*" indicates rejection of the null hypothesis. The critical values for PP test for 1%, 5% and 10% significance levels for model with "c" are -3.43, -2.86, and -2.57; for model with "c,t" are -3.96,-3.41, and -3.13; and for a model with no deterministic trend are -2.56, -1.93, -1.61.

Table 1.3 Johansen Cointegration Test Results

Model 1A: X = (basemetp, indp, cpi, M2, repo, reer)

Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
$r \leq 5$	4.80	8.18	4.82	8.18
$r \leq 4$	11.50	17.95	6.69	14.90
$r \leq 3$	23.20	31.52	11.65	21.07
$r \leq 2$	43.60	48.28	20.41	27.14
$r \leq 1$	77.0*	70.60	33.31	33.32
$r = 0$	125.0*	90.39	48.06*	39.43

Model 1B: X = (precmetp, indp, cpi, M2, repo, reer)

Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
$r \leq 5$	5.50	8.18	5.50	8.18
$r \leq 4$	13.00	17.95	7.50	14.90
$r \leq 3$	23.40	31.52	10.40	21.07
$r \leq 2$	45.60	48.28	22.10	27.14
$r \leq 1$	78.90*	70.60	33.20	33.32
$r = 0$	126.7*	90.39	47.90*	39.43

Model 1C: X = (agricp, indp, cpi, M2, repo, reer)

Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
$r \leq 5$	5.50	8.18	5.47	8.18
$r \leq 4$	12.50	17.95	6.98	14.90
$r \leq 3$	23.60	31.52	11.11	21.07
$r \leq 2$	44.30	48.28	20.77	27.14
$r \leq 1$	72.80*	70.60	28.50	33.32
$r = 0$	123.5*	90.39	50.70*	39.43

Model D: X = (coalp, indp, cpi, M2, repo, reer)

Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
$r \leq 5$	4.50	8.18	4.50	8.18
$r \leq 4$	12.00	17.95	7.50	14.90
$r \leq 3$	24.60	31.52	12.60	21.07
$r \leq 2$	41.40	48.28	16.90	27.14
$r \leq 1$	72.50*	70.60	31.10	33.32
$r = 0$	120.7*	90.39	48.20*	39.43

Notes: "*"indicates rejection of the null hypothesis. The optimal lag length for each model was selected based on AIC. The critical values correspond to 5% significant level.

Table 1.4 Estimated Error Correction Models

Model	Deterministic Trend	Lags	Cointegration Rank
Model 1A (with basemetp)	c,t	2	1
Model 1B (with precmetp)	c,t	2	1
Model 1C (with agricp)	c,t	2	1
Model 1D (with coalp)	c,t	2	1

Notes: The cholesky ordering for all models is (commodity price, indp, cpi, M2, repo, reer).
The number of lags was selected by minimizing the AIC.

Table 1.5 Model Diagnostic Test

Model	Portmanteau Test	ARCH-LM Test	Jarque-Berra
1A	0.97	0.13	0.00*
1B	0.99	0.56	0.00*
1C	0.96	0.60	0.00*
1D	0.86	0.29	0.00*

Notes: "*" indicate rejection of the null. The numbers in the tables are p-values.

Table 1.6 Forecast Error Variance Decomposition for model 1A

Variance Decomposition of Base metal prices (basemetp)						
Period	basemetp	indp	cpi	M2	repo	reer
1	100	0.00	0.00	0.00	0.00	0.00
6	96.62	0.13	0.17	2.85	0.17	0.06
18	87.10	4.89	1.07	6.10	0.67	0.17
24	83.40	6.96	1.64	6.99	0.82	0.20
36	76.20	12.1	1.96	8.66	0.87	0.22
Variance Decomposition of industrial production (indp)						
Period	basemetp	indp	cpi	M2	repo	reer
1	0.08	99.92	0.00	0.00	0.00	0.00
6	21.59	75.10	0.20	1.09	0.25	1.77
18	28.93	65.04	0.23	3.38	0.13	2.29
24	28.84	64.23	0.19	4.10	0.11	2.53
36	28.04	63.55	0.16	5.21	0.09	2.96
Variance Decomposition of consumer price index (cpi)						
Period	basemetp	indp	cpi	M2	repo	reer
1	0.07	0.09	99.84	0.00	0.00	0.00
6	0.26	2.07	96.21	0.08	1.36	0.02
18	0.92	1.17	95.73	0.02	2.14	0.01
24	1.50	0.87	95.44	0.02	2.15	0.01
36	2.49	0.58	94.81	0.01	2.10	0.01
Variance Decomposition of Money Supply (M2)						
Period	basemetp	indp	cpi	M2	repo	reer
1	0.02	0.09	0.17	99.7	0.00	0.00
6	0.56	1.29	0.10	93.5	0.45	4.15
18	13.3	14.9	0.50	65.9	1.68	3.71
24	19.2	19.6	0.67	55.5	1.85	3.22
36	26.1	24.6	0.84	43.9	1.99	2.63
Variance Decomposition of repurchase rate (repo)						
Period	basemetp	indp	cpi	M2	repo	reer
1	0.01	0.43	0.13	0.46	98.98	0.00
6	2.39	6.15	0.02	0.15	88.88	2.41
18	14.6	16.15	0.11	0.06	65.78	3.31
24	18.2	18.83	0.15	0.05	59.54	3.20
36	22.7	22.00	0.22	0.04	52.06	2.99
Variance Decomposition of real effective exchange rate(reer)						
Period	basemetp	indp	cpi	M2	repo	reer
1	2.61	0.03	0.94	0.26	0.42	95.7
6	3.91	3.75	0.39	1.84	1.34	88.8
18	1.73	9.3	0.14	3.23	0.45	85.1
24	1.30	11.4	0.12	3.36	0.36	83.5
36	1.03	14.2	0.12	3.46	0.28	80.9

Notes: Model A is a VECM with the following Cholesky ordering (basemetp, indp, cpi, M2, repo, reer) basemetp is base metal price index, indp is the industrial production, cpi is the consumer price index, M2is money supply and reer is the real effective exchange rate.

Table 1.7 Forecast Error Variance Decomposition for model 1B

Variance Decomposition of precious metal prices (precmetp)						
Period	precmetp	indp	cpi	M2	repo	reer
1	100	0.00	0.00	0.00	0.00	0.00
6	92.35	3.74	0.71	1.02	0.53	1.65
18	69.44	16.82	0.46	3.50	7.38	2.40
24	61.34	22.94	0.48	4.27	8.74	2.22
36	52.79	31.67	0.76	4.94	8.21	1.63
Variance Decomposition of industrial production (indp)						
Period	precmetp	indp	cpi	M2	repo	reer
1	0.97	99.0	0.00	0.00	0.00	0.00
6	1.54	96.2	0.93	0.78	0.44	0.11
18	1.28	73.5	3.01	4.92	15.83	1.43
24	1.01	61.7	3.50	7.24	24.57	2.02
36	0.74	47.5	3.72	11.07	34.75	2.27
Variance Decomposition of consumer price index (cpi)						
Period	precmetp	indp	cpi	M2	repo	reer
1	0.05	0.13	99.82	0.00	0.00	0.00
6	1.07	2.22	95.04	0.06	1.58	0.03
18	1.64	1.31	94.70	0.04	2.23	0.09
24	1.75	0.99	95.12	0.03	1.91	0.19
36	1.83	0.68	95.70	0.02	1.30	0.47
Variance Decomposition of Money Supply (M2)						
Period	precmetp	indp	cpi	M2	repo	reer
1	0.01	0.08	0.19	99.71	0.00	0.00
6	0.92	1.31	0.10	93.95	0.47	3.25
18	1.81	19.38	1.42	69.45	6.57	1.37
24	1.86	23.69	2.40	58.69	11.71	1.65
36	1.57	23.23	3.78	46.32	22.05	3.06
Variance Decomposition of repurchase rate (repo)						
Period	precmetp	indp	cpi	M2	repo	reer
1	0.98	0.21	0.23	0.50	98.07	0.00
6	0.33	5.40	0.05	0.26	93.08	0.88
18	0.46	20.66	2.21	0.21	74.87	1.59
24	0.46	24.98	4.74	0.40	65.07	4.35
36	0.37	25.60	9.78	1.74	51.01	11.51
Variance Decomposition of real effective exchange rate(reer)						
Period	precmetp	indp	cpi	M2	repo	reer
1	0.75	0.20	1.34	0.38	0.24	97.09
6	0.47	1.30	0.55	2.27	1.17	94.25
18	0.45	4.89	0.36	3.65	3.46	87.18
24	0.46	5.76	0.51	3.62	6.00	83.64
36	0.53	6.08	0.84	3.28	11.4	77.83

Notes: Model B has the following Cholesky ordering (precmetp, indp, cpi, M2, repo, reer) basemetp is base metal price index, indp is the industrial production, cpi is the consumer price index, M2 is money supply and reer is the real effective exchange rate.

Table 1.8 Forecast Error Variance Decomposition for model 1C

Variance Decomposition of (agricp)						
Period	agricp	indp	cpi	M2	repo	reer
1	100	0.00	0.00	0.00	0.00	0.00
6	99.3	0.04	0.37	0.00	0.02	0.25
18	96.0	1.88	0.95	0.28	0.09	0.35
24	94.9	2.92	1.17	0.58	0.09	0.32
36	93.0	4.74	1.22	0.68	0.10	0.28
Variance Decomposition of industrial production (indp)						
Period	agricp	indp	cpi	M2	repo	reer
1	0.00	100	0.00	0.00	0.00	0.00
6	13.6	83.5	0.40	0.70	0.54	1.21
18	19.6	74.4	0.54	1.78	1.06	2.65
24	19.5	73.4	0.64	2.27	1.24	2.93
36	18.9	72.3	0.83	3.17	1.55	3.27
Variance Decomposition of consumer price index (cpi)						
Period	agricp	indp	cpi	M2	repo	reer
1	0.01	0.13	99.9	0.00	0.00	0.00
6	0.84	2.14	95.9	0.06	1.05	0.01
18	2.94	0.97	94.3	0.04	1.70	0.03
24	4.14	0.80	93.2	0.05	1.77	0.06
36	6.02	0.84	91.1	0.06	1.82	0.12
Variance Decomposition of Money Supply (M2)						
Period	agricp	indp	cpi	M2	repo	reer
1	0.65	0.00	0.18	99.2	0.00	0.00
6	1.01	2.41	0.10	91.5	0.32	4.61
18	7.89	19.1	0.04	66.5	0.97	5.54
24	11.6	24.9	0.04	56.8	0.93	5.63
36	16.4	31.6	0.04	45.4	0.84	5.65
Variance Decomposition of repurchase rate (repo)						
Period	agricp	indp	cpi	M2	repo	reer
1	0.06	0.96	0.19	0.42	98.38	0.00
6	1.32	9.78	0.07	0.11	86.76	1.96
18	9.26	21.41	0.09	0.14	65.33	3.78
24	11.6	24.43	0.09	0.16	59.66	4.02
36	14.6	28.02	0.09	0.18	52.89	4.24
Variance Decomposition of real effective exchange rate(reer)						
Period	agricp	indp	cpi	M2	repo	reer
1	0.75	0.00	1.03	0.18	0.47	97.57
6	1.55	2.83	0.49	1.13	1.48	92.52
18	0.66	6.46	0.27	1.93	0.47	90.21
24	0.49	7.76	0.25	2.03	0.34	89.12
36	0.39	9.58	0.22	2.14	0.22	87.45

Notes: Model C has the following Cholesky ordering (agricp, indp, cpi, M2, repo, reer) basemetp is base metal price index, indp is the industrial production, cpi is the consumer price index, M2 is money supply and reer is the real effective exchange rate

Table 1.9 Forecast Error Variance Decomposition for model 1D

Variance Decomposition of (coalp)						
Period	coalp	indp	cpi	M2	repo	reer
1	100	0.00	0.00	0.00	0.00	0.00
6	98.36	0.32	0.59	0.15	0.53	0.05
18	85.24	1.15	0.88	0.93	7.68	4.12
24	76.96	3.20	0.79	1.38	11.04	6.62
36	67.67	8.13	0.63	1.90	13.5	8.21
Variance Decomposition of industrial production (indp)						
Period	coalp	indp	cpi	M2	repo	reer
1	1.05	98.95	0.00	0.00	0.00	0.00
6	3.61	92.85	1.92	1.07	0.28	0.27
18	8.53	70.92	2.50	4.08	7.79	6.18
24	14.44	59.08	2.23	5.29	10.40	8.56
36	21.83	48.10	1.96	7.11	11.69	9.31
Variance Decomposition of consumer price index (cpi)						
Period	coalp	indp	cpi	M2	repo	reer
1	0.22	0.01	99.76	0.00	0.00	0.00
6	0.27	0.58	97.83	0.07	1.15	0.10
18	0.33	0.83	96.31	0.10	2.29	0.15
24	0.39	1.50	95.60	0.10	2.10	0.31
36	0.29	2.42	94.60	0.08	1.51	1.10
Variance Decomposition of Money Supply (M2)						
Period	coalp	indp	cpi	M2	repo	reer
1	0.03	0.02	0.19	99.76	0.00	0.00
6	1.45	1.50	0.10	94.15	0.47	2.33
18	1.09	14.55	0.17	76.56	6.04	1.58
24	2.02	17.04	0.22	67.58	9.71	3.43
36	5.13	16.08	0.21	55.79	15.11	7.68
Variance Decomposition of repurchase rate (repo)						
Period	coalp	indp	cpi	M2	repo	reer
1	0.58	0.56	0.21	0.52	98.14	0.00
6	0.12	7.66	0.04	0.22	91.28	0.69
18	1.13	21.65	0.26	0.14	74.52	2.30
24	3.81	24.36	0.31	0.13	65.23	6.16
36	10.95	23.85	0.29	0.21	50.76	13.93
Variance Decomposition of real effective exchange rate(reer)						
Period	coalp	indp	cpi	M2	repo	reer
1	4.37	0.01	0.80	0.39	0.57	93.86
6	4.60	1.21	0.31	1.81	1.61	90.47
18	4.37	3.51	0.13	2.50	2.45	87.06
24	6.22	3.80	0.10	2.46	3.95	83.46
36	10.2	3.56	0.07	2.29	6.50	77.37

Notes: Model D has the following Cholesky ordering (coalp, indp, cpi, M2, repo, reer) basemetp is base metal price index, indp is the industrial production, cpi is the consumer price index, M2 is money supply and reer is the real effective exchange rate.

Chapter 2 - Effects of Commodity Price Shocks On the Economic Sectors in South Africa

2.1 Introduction

The dependence of the South African economy on commodities has been reported in research papers, policy analyses documents, and in the media[20]. Commodities have played a very important role in the economy since diamonds and gold were discovered in the late 19th century. According to Citibank, the South African mineral endowment is estimated at about $2.5 trillion, ranking the country as the world's largest endowment (Antin, 2013). In terms of its impact on the economy, the mining sector in South Africa accounts about 18% of the country's GDP and about 50% of the total merchant exports. It provides about 1.3 million jobs, and mining companies alone pay about 17.2% of total corporate taxes (Antin, 2013). This large endowment in commodities, minerals in particular, has allowed the country to benefit from the increase in global commodity demand and prices that has been happening in the last decade. However, this commodity price boom did not significantly improve the lives of the mining workers, which has led to persistent labor unrest (Antin, 2013).

A related issue is that the gains in the mining sector have not been felt in other sectors of the economy. One explanation for this could be the fact that a considerable amount of South African mineral resources are exported as raw ores or are only partially processed[21]. Another reason is that a relatively strong South African Rand has had a negative impact on some of the sectors, like the manufacturing sector, and other sectors that have not benefitted from the commodity price boom. This phenomenon, known as "Dutch Disease", has been a topic for research in South Africa[22].

Despite the importance of the mining sector and its potential, there is a belief among policy makers in South Africa that the global commodity boom did not fully benefit the country's economy in general (Antin, 2013). In order to ensure a better and inclusive contribution of the mining sector in the overall economy, the South African government adopted the New Growth

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[20] For the dependence of the South African economy on commodities see Ocran and Biekpe (2007), Sujithan et. al (2013), Chen et al. (2014), and Mallick and Sousa (2012).
[21] For more details on this see Davis (2010).

[22] For example see Frankel (2007).

Path (NGP) that identifies mineral beneficiation as one of the priority growth nodes intended to accelerate manufacturing, job creation, and add value to exports.

Despite the importance that the mining sector plays in the South African economy, no study has been undertaken to identify the linkages that the mining sector has with other sectors of the economy. So, this study closes the gap by analyzing the impact of the fluctuation in commodity prices on the mining and manufacturing sectors output and employment. Specifically, the study tries to answer the following three questions: (1) What effect do commodity price fluctuations have on production and employment in the mining sector? (2) What impact do commodity price fluctuations have on production and employment in the manufacturing sector? (3) How do shocks to different commodities differ in terms of their impact on the economic sectors?

To answer these questions a vector autoregressive (VAR) model technique is employed. In the first VAR model, the effects of each of the four commodity prices and price indices on production and employment are analyzed. The indices include the base metal price index[23] , precious metal price index[24] , agricultural commodity price index[25] , and coal prices[26]. The second model, consisting of another 3 equation-VAR for commodity prices, mining production, and manufacturing production, is employed to study the impact of mining production on manufacturing. The results indicate that both the mining and manufacturing sectors benefitted from the commodity price boom, with higher benefits accruing to the manufacturing sector.

The chapter is organized as follows: Section 2.2 reviews recent work on sector impact of commodity price changes, section 2.3 describes the data and the methodology; section 2.4 presents the results; and section 2.5 provides conclusions.

2.2 Literature Review

The impact of commodity prices, such as oil and natural gas, on sector performance has been a topic of research. Hanson et al. (1993) use an input-output model and CGE model to analyze the direct and indirect cost linkages between energy and other sectors of the economy, allowing for sectorial output adjustment and the effects on the U.S current account. They find that the effects

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[23] The base metal price index is composed of aluminum, copper, iron ore, lead, nickel, Tin and Zinc prices.

[24] The precious metal price index consists of gold, platinum and silver prices.

[25] The agricultural commodity price index consists of food, beverages, and agricultural raw material prices.

[26] The coal prices are South African Thermal coal prices.

on agriculture are not limited to the direct and indirect energy costs. Exchange rate or foreign borrowing adjustments to higher oil import costs and government support programs for agriculture also matter.

Torul and Alper (2010), using a VAR model and monthly data from 1990 to 2007, investigate the relationship between oil prices and the manufacturing sector in Turkey. They find that while oil price increases do not significantly affect the manufacturing sector in aggregate terms, some sub-sectors are adversely affected.

Bolaji and Bolaji (2010) investigate the effects of price increases in different types of petroleum products on manufacturing companies in Nigeria. They find that price increases of petroleum products affects the cost and quantity of raw materials. Those increases reduce production capacity of some companies and reduce the market demand of products, causing a reduction in profit or rate of turnover.

Sharri et al. (2013) study the sectorial impact of oil prices in Malaysia. Using quarterly data from 2000 to 2011, they find that oil prices Granger cause construction GDP, agricultural GDP, and manufacturing GDP.

This literature that analyzes the sectorial impact of commodity price changes has focused mainly on the effect of energy commodities, especially on the effect of oil price changes[27]. The effect of non-energy commodity price fluctuations on economic sectors has received very little attention.

Knop and Vespignani (2014) use quarterly data from 1993 to 2013 to analyze the impact of different commodity prices on the Australian economic sectors. They find that commodity price shocks affect the mining, construction, and manufacturing industries, but have no effect on the financial and insurance sector.

The current study contributes to the existing literature by analyzing the impact of non-oil commodity price fluctuations on the production and employment in manufacturing and mining sectors, in a resource rich country, South Africa. This is important because not only because of the declining level of the employment in the manufacturing sector as it is shown in figure 2.10 shows,

[27] Other studies include Forsyth and Kay (1981), Hutchison (1994), Keane and Prasad (1996) and Bjørnland (1998) and Guidi (2010).

but also, as figure 2.11 indicates, unemployment is a very serious economic challenge facing the South African economy, hence knowing how fluctuations in commodity price levels affect the employment in different sectors, hence in the economy in general is a very important macroeconomic problem.

2.3 Analytical Framework

This section analyzes the data and the methodology used in this research, including unit root tests, cointegration tests, VAR, Granger-Causality, impulse response, and forecast error variance decomposition.

2.3.1 Data, Description and Source

This study uses quarterly data spanning from 1970:1 to 2013:4. The series include industrial production for the mining sector (mineprod), industrial production for the manufacturing sector (manufprod), mining sector employment (minemploy), manufacturing sector employment (manufemploy), base metal price index (basemetp), precious metal price index (precmetp), agricultural commodities price index (agricp), and coal prices (coalp).

The data on sectors' industrial production and employment were obtained from International Financial Statistics of the International Monetary Fund (IFS-IMF). The commodity price and price indices[28] were obtained from the World Bank Commodity Price Data (Pink Sheet). All variables were transformed into natural logarithm form. Figure 2.1 in the appendix illustrates the behavior of the series for the study period. Fig 2.1 shows that production in the manufacturing sector has been increasing slightly over time, whereas production in the mining sector has been more volatile. Both series show a decline around 2008, as a result of the global financial crises. The employment level in the mining sector shows a decline in the late 1980s but started increasing around 2000.

The employment in the manufacturing sector has been declining over time and has been fluctuating more than the employment in the mining sector. The commodity prices show a behavior similar to that of employment in the mining sector, decreasing until 2000 and then increasing steadily. All series show a decline around 2008, reflecting the effect of the global financial crisis.

[28] For all price indices (2010=100).

2.3.2 Unit Root Test

It is customary in time series analysis to start by determining the properties of the data. The first of these analyses involves determining the stationarity property of the data. A time series is said to be stationary if its mean and variance are constant over time (Enders, 2010). It is important to determine if a series is stationary or non-stationary, because with a nonstationary series the assumptions of classical linear regression model are no longer satisfied and can lead to incorrect conclusions. By nature, most macroeconomic series tend to be non-stationary.

There are several tests in the literature[29] that can be used to determine if a series is stationary or not. The most widely used test for the presence of unit root is the Augmented Dickey Fuller (ADF) test. Given the pth order autoregressive process[30]

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \varphi_1 \Delta y_{t-1} + \ldots + \varphi_{p-1} \Delta y_{t-p+1} + \epsilon_t \qquad (2.1)$$

where $\epsilon_t \sim iid(0, \sigma_\epsilon^2)$

The ADF test has a null hypothesis that $\gamma = 0$, against the alternative that $\gamma < 0$. If the test statistic is smaller in absolute terms than the critical value, then we fail to reject the null and conclude that the series has a unit root, indicating that the series is non-stationary. If the test statistic is larger than the critical value, in absolute terms, we reject the null hypothesis and conclude that the series is stationary. As it was mentioned earlier, most macroeconomic series are non-stationary. In order to make the series stationary, the literature recommends transforming the data[31] . If a series has to be differenced d times to make it stationary, the data is known as being integrated of order d.

One important issue in implementing the ADF test is the choice of the optimal lag length. The standard norm in the literature is to select the lag length so that the error in equation 1 is a white noise process. There are several methods suggested in the literature that can be used to choose the optimal value of p. The most widely used techniques involve choosing the value of p

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[29] See Maddala and Kim (1998), Elder and Kennedy (2001), and Glynn et al. (2007) for a survey on different tests.

[30] $\Delta Xt = Xt – Xt-1$. Usually, the value of p is determined using information criteria, like Akaike or SIC. For more details on the information criteria refer to the next section 1.3.2.

[31] The data transformation involves detrending and differencing for a trend stationary series and difference stationary series, respectively. For more details on this see Enders (2010).

in order to minimize a certain information criteria, such as Akaike and Shwartz Information criteria. In this study we use Akaike Information Criteria (AIC) to choose the value of p.
Another test of unit root which is also commonly used in the literature and also used in this chapter is the Philips-Perron (PP) test, which is identical to the ADF but it uses the Newey–West (1987) heteroskedasticity as well as autocorrelation-consistent covariance matrix estimator to correct the test statistic for heteroskedaticity and serial correlation. A detailed description of the PP can be found in section 1.3.2.

2.3.3 Cointegration Test

Once the order of integration is determined, the next procedure in VAR analysis is to determine if the series are cointegrated. If two or more series are non-stationary, but a linear combination among them is stationary, then the series are said to be cointegrated, meaning that there is a long-run equilibrium relationship among the variables. Determining if the variables are cointegrated is important to determine the right VAR model to be employed. If the variables are cointegrated, then an error correction term has to be included in the VAR.

The most common cointegration method used in the literature is the Johansen cointegration approach. The method is based on the maximum likelihood estimation of a VAR process, and it consists of determining the number of cointegrating vectors. The Johansen cointegration method uses two types of tests, trace and maximum eigenvalue, given in equations 2.2, and 2.3, respectively.

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{k} \ln(1-\hat{\lambda}_i) \tag{2.2}$$

$$\lambda_{\max}(r, r+1) = -T\ln(1-\hat{\lambda}_{r+1}) \tag{2.3}$$

The null hypothesis for the trace test is that there is at most "r" cointegrating vectors. The null hypothesis for the maximum eigenvalue test is that the number of cointegrating vectors is "r". For both tests, the alternative hypothesis is that the number of cointegrating vectors is "r+1".
Where $\hat{\lambda}_i$ is the estimated characteristic root, and T is the number of observations. As it was explained in chapter one, testing for cointegration is important because if two or more series are non-stationary and cointegrated, then a Vector Autoregressive (VAR) model is miss-specified

since there is a long-run co-movement between the series. In this case, an error correction term needs to be included in the VAR.

2.3.4 Vector Autoregressive Model

In order to determine the dynamic impact of commodity price fluctuations on the mining and manufacturing production and employment, I employ the Vector Autoregression (VAR) model. The VAR model, which originally was proposed by Sims (1980), is a dynamic system of equations where the dependent variable is a function of its own lags and the lags of the other variables in the model, while imposing a minimal number of assumptions about the underlying structure of the economy. Given a vector Xt of endogenous variables, the structural representation of the VAR (p) model can be expressed as follows:

$$\Gamma_0 X_t = \lambda + \sum_{i=1}^{p} \Gamma_i X_{t-i} + B\varepsilon_t \tag{2.4}$$

Pre-multiplying both sides of equation 2.4 by Γ_0^{-1} we get the reduced form VAR given by
where, Xt = [commodity price, industrial production, employment] is 3x1 column matrix of the endogenous variables, Γ_0 is an invertible 3x3 contemporaneous matrix, Γ_is are 3x3 autoregressive coefficient matrices, B is a 3x3 matrix of structural coefficients representing the instantaneous effects of the structural shocks, and $\mathcal{E}_t$ is a 3x1 column vector of structural disturbances, which are assumed to be white noise, with a covariance matrix $\Sigma\mathcal{E} = E[\mathcal{E}_t\mathcal{E}'_t]$.
Pre-multiplying both sides of equation 2.4 by Γ_0^{-1} we get the reduced form VAR given by

$$X_t = A_0 + \sum_{i=0}^{p} A_i X_{t-i} + e_t \tag{2.5}$$

where, $A_0 = \Gamma_0^{-1}\lambda$, $A_i = \Gamma_0^{-1}\Gamma_i$, and $e_t = \Gamma_0^{-1}B\mathcal{E}_t$, is a white noise process, with a nonsingular covariance matrix Σe. The A_is and Ω in the reduced form VAR can be estimated using OLS. Once we have estimated the reduced form VAR for X_t, we need to recover the structural parameters, since it is the structural shocks that have economic interpretations, and not the reduced form model shocks. There are different procedures used to uncover the structural parameters from the reduced form model. In this study, the structural shocks are recovered using Cholesky decomposition of the variance-covariance matrix of the reduced form VAR residuals. The Cholesky decomposition is a recursive structure that assumes that Γ_0 is an identity matrix, and B is a lower triangular matrix. This implies that the relationship between reduced VAR disturbances and the structural disturbances is expressed in the following system of equations[32].

$$\begin{bmatrix} \mathcal{E}_t^{comp} \\ \mathcal{E}_t^{indp} \\ \mathcal{E}_t^{employ} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ a_{2,1} & 1 & 0 \\ a_{3,1} & a_{3,2} & 1 \end{bmatrix} \begin{bmatrix} e_t^{comp} \\ e_t^{indp} \\ e_t^{employ} \end{bmatrix} \tag{2.6}$$

The Cholesky ordering above implies that a commodity price shock only responds to its own shocks, and shocks to industrial production and employment do not have a contemporaneous effect on commodity prices. This can be explained by the fact that commodity prices are determined in the world market and thus are less endogenous than the other two variables. The second row implies that industrial production responds contemporaneously to commodity prices shocks, but not to employment shocks. Finally, the last row implies that employment responds contemporaneously to shocks in both commodity prices and industrial production.

Another important consideration in estimating a VAR model is the number of lags to be included in the model. In the above model, this implies determining the optimal value of p that will be used in the model, while at the same time ensuring that the model satisfies the diagnostic tests.

To assess the impact of commodity price on production and employment in the mining and manufacturing sectors, impulse response function, Granger-Causality, and variance decomposition techniques are used.

2.3.5 Granger-Causality Test

One of the tests that is often used in macroeconomic analysis is the Granger causality test. Given two stationary variables X_t and Y_t. X_t is said to Granger-cause another, Y_t, if Y_t can be predicted with greater accuracy by including past values of X_t, (Granger, 1969). The test for a bivariate VAR model can be shown in the following system of equations[33] :

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[32] e_t^{comp} is the commodity price shocks, e_t^{indp} is the industrial production shocks, and e_t^{employ} is the employment shocks.

[33] e_t and $\mathcal{E}_t$ are the error terms, i's are the optimal number of lags which can be obtained by minimizing the information criteria (Akaike or SIC), and t is the time period.

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{q} \beta_i X_{t-i} + e_t \tag{2.7}$$

$$X_t = \theta_0 + \sum_{i=1}^{p} \delta_i X_{t-i} + \sum_{i=1}^{q} \rho_i Y_{t-i} + \varepsilon_t \tag{2.8}$$

The null hypothesis that X_t does not Granger-cause Y_t, is βi = 0, and the alternative that X_t does Granger-cause Y_t, βi ≠ 0. Similarly, the null hypothesis that Y_t does not Granger X_t, is ρi = 0, against the alternative that Y_t does Granger cause X_t, ρi ≠ 0. When both null hypotheses are rejected, then there is a two-way Granger causality, otherwise we say there is a one-way causality.

2.3.6 Impulse Response Function and Forecast Error Variance Decomposition

Having estimated and identified a VAR model, researchers are often interested in obtaining the impulse response functions (IRF) and forecast error variance decomposition (FEVD). IRF and FEVD analyses are standard tools for investigating the relationship between variables in a VAR model. Impulse responses trace out the response of current and future values of each of the variables to a one-standard deviation increase in the current value of one of the VAR errors.

Starting from the reduced VAR in equation 2. 5, we can express the model in vector moving average (VMA) form, given in equation 2.9.

$$X_t = A_0 + \sum_{i=0}^{\infty} A_1^i e_{t-i} \tag{2.9}$$

which in turn can be expressed using the structural errors, as:

$$X_t = A_0 + \sum_{i=0}^{\infty} \psi_i \mathcal{E}_{t-i} \tag{2.10}$$

So, the graph of ψ_i at different time paths yields the impulse response of each variable in the system from different structural shocks. Another important use of the VAR is the forecast error variance decomposition. FEVD shows the proportion of the forecast error variance of the endogenous variables that is due to each of the shocks. If $\mathcal{E}$x,t explain none of the forecast error variance of {yt} at all forecast horizons, then the yt is exogenous.

2.4 Analysis of Results

2.4.1 Unit Root Test

Table 2.1 and 2.2 present the estimates of the unit root test for the series in levels, as well as in first differences for the ADF and PP, respectively. The ADF and PP results show that for all the series the null hypothesis of non-stationarity is not rejected when the series are in levels. However, the null hypothesis is rejected for all the series when the series are transformed by taking the first difference; hence, the series become stationary upon taking the first difference. This implies that all the series are integrated of order one. Since all the series are integrated of the same order, then the use of the Johansen cointegration test is appropriate.

2.4.2 Cointegration Test

Once the order of integration of the series has been determined, cointegration test was conducted. As it was stated in the previous section, if two or more series are cointegrated then there is at least one linear combination of the series in the model that is stationary, even if individually the series are non-stationary. The Johansen cointegration test is used to determine the number of cointegrating vectors. The results of the cointegration tests for the manufacturing and mining sectors are presented in tables 2.3 and 2.4, respectively. The results from table 2.3 indicate that for all four models studied, the test statistics are less than their respective critical values. This indicates that there is no cointegration for both the trace and maximum eigenvalue tests, hence we conclude that there is no single cointegration vector in the model.

Similar to the results shown in table 2.3, the results in table 2.4 indicate no sign of contegration relation among the series in all four models analyzed for the mining sector. This implies that there is no linear combination among the variables in all models that is stationary. The absence of any cointegration relation in all the models implies that the use of unrestricted VAR is appropriate to analyze the dynamic relationship among the variables in the models. One important step in estimating a VAR model is determining the lag length. The optimal lag lengths were selected by minimizing the AIC and are reported in table 2.5. Table 2.5 also shows the constant, time trend, and deterministic trends included in the models.

2.4.3 Model Diagnostics

Once a VAR model is employed for a dynamic relationship among the variables, it is often checked to determine if it represents the data generating process (DGP) adequately. There are many diagnostic methods used in the literature, but the most used determine whether the estimated residuals satisfy the white noise assumption. This study uses residual-based tests, such as the Portmanteau test, the LM test, and the Jarque Berra test. The Portmanteau test checks whether the estimated residual autocovariances are zero, whereas the LM tests the residuals autocorrelation, and the Jarque-Berra test checks if the residuals are normally distributed. A more detailed description of these tests can be found in section 1.3.5, in chapter one of this disswrtation.

The results of the diagnostic tests are presented in tables 2.6. For the manufacturing sector, the lowest p-value for the Portmanteau test is 0.12 for model A. Since this p-value is larger than 0.05, we fail to reject the null hypothesis that the errors of the estimated model are not autocorrelated. Similarly, the smallest p-value for the LM test for the estimated models in the manufacturing sector is 0.32 for model D. This implies that we fail to reject the null hypothesis and conclude there is no evidence of residual autocorrelation. Similarly, for the mining sector, the smallest p-value \for the Portmanteau test is 0.18 for model D. Because the p-value is larger than 0.05, we fail to reject the null hypothesis that the errors of the estimated models do exhibit autocorrelation. The results of the LM test for the mining sector also suggest that we fail to reject the null hypothesis that the errors are not autocorrelated. The results of the Jarque-Berra test, on the other hand, indicate that for all models estimated we should reject the null hypothesis that the errors are normally distributed. Despite the lack of evidence that the errors are normally distributed, because of the favorable results of the LM and Portmanteau tests, we conclude that the estimated VAR models are acceptable.

2.4.4 Granger-Causality Test

The Granger-causality results for the manufacturing sector are presented in table 2.7, and those of the mining sector are presented in table 2.8. The results are presented in terms of F-statistics and p-values. For the manufacturing sector, the results indicate that there is a two-way Granger causality between base metal prices and industrial production, but there is one way causation from base metal to employment level in the sector. Similarly, precious metal prices Granger-cause manufacturing production, but no reverse causality is observed. Results also show that there is no Granger-causality between precious metal prices and employment in the manufacturing sector. Manufacturing production does Granger-cause the level of employment in the manufacturing sector, but there seems to be no reverse causation.

There is a one way causation from agricultural commodity prices to the industrial production in the manufacturing sector, but no Granger causation exists between agricultural commodity prices and employment in the manufacturing sector. Finally, there is a one way Granger-causation from manufacturing production to coal prices. Like other commodity prices, there is no Granger-causality between coal prices and employment in the manufacturing sector.

For the mining sector, results suggest that there is one way causality from base metal prices to the industrial production and one-way causation from base metal prices to employment in the sector. Contrary to the manufacturing sector, the results indicate that there is no Granger causality at the 5% significance level between precious metal prices and production in the mining sector, nor between precious metal prices and employment.

Results indicate that there is a one-direction causation from agricultural commodity prices to production in the mining sector, but no causality between agricultural prices to employment in the mining sector. Coal prices do Granger-cause production in the mining sector, but there is no causation between coal prices and employment in the sector. Finally, results indicate that there is Granger causality from employment to production in the mining sector, but no reverse causality exists, at the 5 % significance level.

2.4.5 Impulse Response Functions

In the following section, we analyze the impulse responses based on four 3-VAR models. The impulse response analysis is based on the impact of a positive one standard deviation shock of the four commodity prices (basemetp, precmetp, agricp, and coalp) on the production level and employment in the manufacturing and mining sectors. Confidence intervals at the 95% level are computed for the impulse responses using bootstrap methods. We follow the standard percentile interval method as described in Breitung et al. (2004) with 1000 bootstrap residuals. The results of the impulse response functions for the manufacturing and mining sectors are presented in figures 2.2 through 2.9.

Figure 2.2 shows the results of the impulse response function for model A in the manufacturing sector. Results reveal that an unexpected increase in the base metal prices (basemetp) results in an immediate increase in production in the manufacturing sector (manufprod). The increase in the production reaches its peak after two quarters, and then the effect starts fading. Similarly, a positive shock in the base metal prices has an immediate increase in the employment level in the manufacturing sector (minemploy), reaching its peak after 5 quarters, after which the effect dissipates. Comparing the IRFs, it appears that the impact of a positive shock of base metal prices has a larger impact on production than it does on employment in the manufacturing sector. As expected, a shock to production in the manufacturing sector has a positive but rather small effect on base metal price. Since South Africa is a small country, internal shocks should have negligible effect on the commodity prices, which are mainly determined in the world market.

Figure 2.3 presents the impulse response functions for model A for the mining sector. Similar to the manufacturing sector, the results show that a positive shock to base metal prices has a positive impact on the level of production and employment in the mining sector. However, a closer inspection of the IRF suggests that the impact of the shock to base metal prices has a much smaller effect on the mining sector compared to the effects on the manufacturing sector. Similarly, the effect of a positive shock of employment on production is almost negligible, as is the effect of a positive shock of production on employment. Finally, the effect of a positive shock of production in the mining sector on the price of base metal price is negative but small.

Figure 2.4 shows the impulse response function for model B in the manufacturing sector. Results show that a positive shock to precious metal prices (precmetp) has a positive impact on the production as well as the employment level in the manufacturing sector. The effect on production appears to be slightly larger than the effect on employment. The peak on the production level is reached after two quarters, while the peak on the employment level is reached after three quarters, after which the effects start dying down. Figure 2.5 presents the impulse responses from model B for the mining sector. The effect of a positive shock to precious metal price on production and employment in the mining sector are both small and identical, whereas the effect of a positive shock to production in the mining sector has a relatively larger effect on the precious metal prices.

An unexpected increase in the agricultural commodity prices, shown in figure 2.6, has an immediate and increasing impact on the production level in the manufacturing sector. After two periods, the impact peaks, and the effect declines gradually. Employment in the manufacturing sector also responds positively to a positive shock in agricultural commodity prices. In terms of magnitude, the impact of the shock on employment is much smaller than the effect on production, and it reaches the highest effect in three periods then declines gradually. A positive shock to agricultural commodity prices (Figure 2.7) has a positive effect on both production and employment in the mining sector. As in the other shocks, the effect of the agricultural commodity price shock on employment is smaller than the effect on production.

Finally, figures 2.8 and 2.9 show the effects of shocks to coal prices in the manufacturing and mining sectors, respectively. A positive shock to coal prices has a small and brief positive effect on production in the manufacturing sector (Figure 2.8). The impact is positive for the first quarter, and then it starts declining and becomes negative. In the sixth quarter, the coal price shock reaches its maximum negative effect, and then the negative effect starts dying out. The effect of the shock on employment is similar to the effect of the same shock on industrial production. The positive coal price shock causes an initial increase in the employment level, reaching the peak in one quarter and becoming negative in less than 2 quarters. The effect of the shock reaches its trough in the 6th quarter, and then the negative effect disappears. One possible interpretation of this negative impact of the coal price shock on production and employment in the manufacturing sector is the fact that coal is the most important source of energy, an important input in the manufacturing sector. Thus, higher coal prices will lead to higher production costs, leading to lower production and employment in the manufacturing sector. In the mining sector, figure 2.9 shows that a positive shock to coal price has a positive effect on mining production and employment levels. Initially, the unexpected increase in the price causes production in the mining sector to increase for one quarter and then decline to its original level. Similarly, a shock to the coal price leads to an increase in the employment level for a quarter, and then it starts declining until it reaches its original level.

Overall, the results from the impulse response functions are consistent with the Granger causality results. Commodity price shocks in the impulse response analysis that indicate a small and insignificant effect on production and employment levels are associated with corresponding lack of causality in the Granger-causality analysis.

2.4.6 Forecast Error Variance Decomposition

The variance decomposition shows the proportion of the forecast error in a given variable that is explained by the variations of itself and the variations of the other variables in the model.

For the purpose of this study, variance decomposition is used to measure the portion of the manufacturing and mining sectors production and employment that are attributed to the variations in the prices of the four commodities. The results of the variance decomposition analysis for the manufacturing sector for the four models are presented in tables 2.9 through 2.12, and tables 2.13 through 2.16 for the mining sector.

The results from the top panel of all of the tables reveal that the variations in the commodity prices were almost entirely accounted for by its own shocks. For all models, in both sectors, 100 percent of the variation in the prices is explained by its own shock in the first period following the shock in commodity prices. Although the importance of the commodity price in explaining its own variation declines with time, even after twelve quarters the lowest fraction of the forecast error that is accounted for by its own shock is 84.71 percent (Table 2.14). This result reflects the higher level of exogeneity of the commodity prices in the model.

Table 2.9 shows that base metal prices account for a significant variation in the production and employment levels in the manufacturing sector. The variation in production in the manufacturing sector that is explained by variations in the base metal prices ranges from 2.87% in the first quarter to about 31.6 % by the 12th quarter. For the employment level, changes in base metal prices account for about 2.89 % in the first quarter and about 17.23% by the end of the 12th quarter. This rather large impact of base metal prices on the manufacturing sector is explained by the fact that base metals are used as inputs in the manufacturing sector.

Table 2.10 shows that precious metal prices explain very little variation in production and employment in the manufacturing sector. After 12 quarters variations in the precious metal prices account for 3.76 % and 0.86% of the variations in the production and employment levels, respectively. Clearly, the change in the precious metal price accounts for a minimal portion of the variation in the production and employment levels in the manufacturing sector. This result can be explained by the fact that precious metals are mainly exported with minimum or no added value, hence its minor contribution in the manufacturing employment level, (Davis, 2010).

Table 2.11 shows that variations in agricultural commodity prices account for a considerable amount of the variation in production and employment in the manufacturing sector. In quarter one, changes in agricultural commodity prices account for 2.13 % of the change in production level and 0.10% of the change in employment. Whereas in period 12, agricultural commodity prices account for about 18%, and 5% of the changes in the production and employment levels, respectively. Finally, table 2.12 shows that, as in the previous cases analyzed, the change in coal prices has a larger effect on the production level than on the employment level in the manufacturing sector. In quarter 1, changes in coal prices account for about 6.26% and 1.84 % of the changes in the production and employment levels, respectively. By quarter 12, only 3.19% of the changes in production and 1.28% variations in employment are attributed to variations in coal prices.

Table 2.13 shows that changes in base metal prices have a considerable amount of impact on the variations in the production and employment levels in the mining sector. However, the impact is smaller in the mining sector when compared to the impact in the manufacturing sector. The results indicate that, in period 1, about 0.84% of the variation in mining production and 2.76 % of the variation in employment are accounted for by variations in the base metal prices. By period 12, base metal prices accounted for 14.39% and 6.79% of the variations in the production and employment levels, respectively. The variations of production and employment in the mining sector due to changes in the precious metal prices, shown in table 2.14, indicate that changes in the precious metal prices have little effect on production and an even smaller effect on employment in the mining sector. The changes in production and employment that are accounted for by changes in precious metal prices in period 1 are 2.68% and 0.51%, respectively. In period 12, the effect of the precious metal prices on changes in production and employment in the sector are 7.03 % and 5.69 %, respectively.

Tables 2.15 and 2.16 show the variations in mining production and employment accounted for by changes in agricultural commodity prices and coal prices, respectively. In table 2.15, the variations of mining production due to changes in agricultural commodity prices is 0.10 % in period 1 and 3.99 % in period 12. For the employment level, agricultural commodity price changes account for 0.15% and 2.10 % for periods 1 and 12, respectively. Clearly variations in agricultural commodity prices have some effect on the variations in production and employment in the mining sector. Table 2.16 indicates that the variations in production and employment in the mining sector that are accounted for by changes in coal prices are very small as well. In period 1, changes in coal prices accounted for 0.23 % and 2.28% variations in production and employment in the mining sector; in quarter 12, the figures were 1.21% and 6.28%, respectively.

Overall, the results indicate that shocks to commodity prices explain a larger amount of the variation in both production and employment in the manufacturing sector than those shocks do in the mining sector. Within the mining sector, shocks to commodity prices tend to explain the variations in the production level more than the changes in the employment levels. Two explanations for these finding are discussed. First, as graph 2.10 indicates, the mining sector in very capital intensive compared to the manufacturing sector. This implies that, ceteris paribus, the mining sector would be less responsive to an increase in commodity prices than the manufacturing sector, which is more labor intensive. One explanation of the lack of responsiveness of employment to commodity prices is the fact that the South African labor market is highly unionized. According to Banerjee et al. (2008), the mining and manufacturing sectors are two of the most unionized sectors in the country, with about 80 percent of the employees in the mining sector and 60 percent in the manufacturing sector unionized between 1995 and 2001. This higher rate of unionization of the labor market imposes higher costs, such as wages and firing costs, making firms less likely to add labor due to commodity prices increases. In his study on South African unemployment, Magruder (2012) also finds central bargaining decreases employment in a sector by eight to 10 percent, especially for small firms.

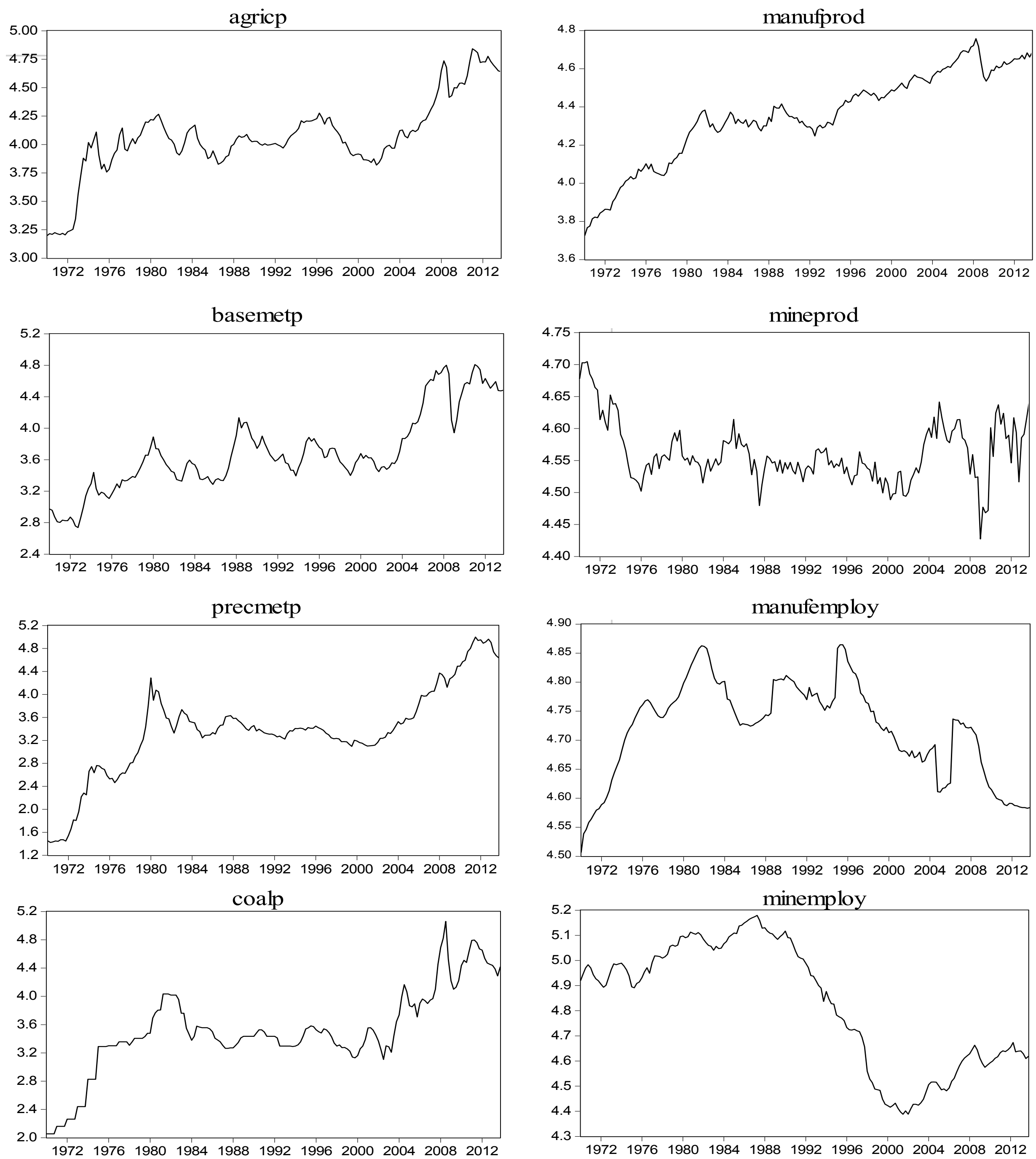
One possible reason that the mining sector is less responsive than the manufacturing sector to changes in commodity prices could be that by nature the mining sector is more capital intensive. As figure 2.9 shows, the South African mining sector is very capital intensive, hence it does not respond much to commodity price shocks.

2.5 Conclusion

The literature suggests that increases in commodity prices could harm some sectors of commodity-exporting countries. This notion is known as “Dutch disease”. To determine the impact of the recent boom in commodity prices and whether Dutch disease has been a major problem in South Africa, this chapter carried out an empirical investigation of the impact of commodity price shocks on production and employment performance in the manufacturing and mining sectors. Four commodity prices were used: base metal price index (basemetp), precious metal price index (precmetp), agricultural commodity price index (agricp), and coal prices. Granger-causality, IRF, and variance decomposition techniques were used. The results indicate that both the mining and manufacturing sectors benefitted from the commodity price boom, with higher benefits accruing to the manufacturing sector. This implies that the decline in the manufacturing sector employment and higher levels of unemployment in South Africa are not a result of a Dutch disease. As the results indicate, overall commodity price shocks tend to have a larger effect in the manufacturing sector than in the mining sector. Two explanations are advanced for this finding. By its nature, the mining sector is more capital intensive, making it less responsive to increases in demand (higher prices). The second explanation could be because the mining sector of the South African labor market is highly unionized. Thus, employers may be very cautious in using more labor in response to higher demand (higher commodity prices).

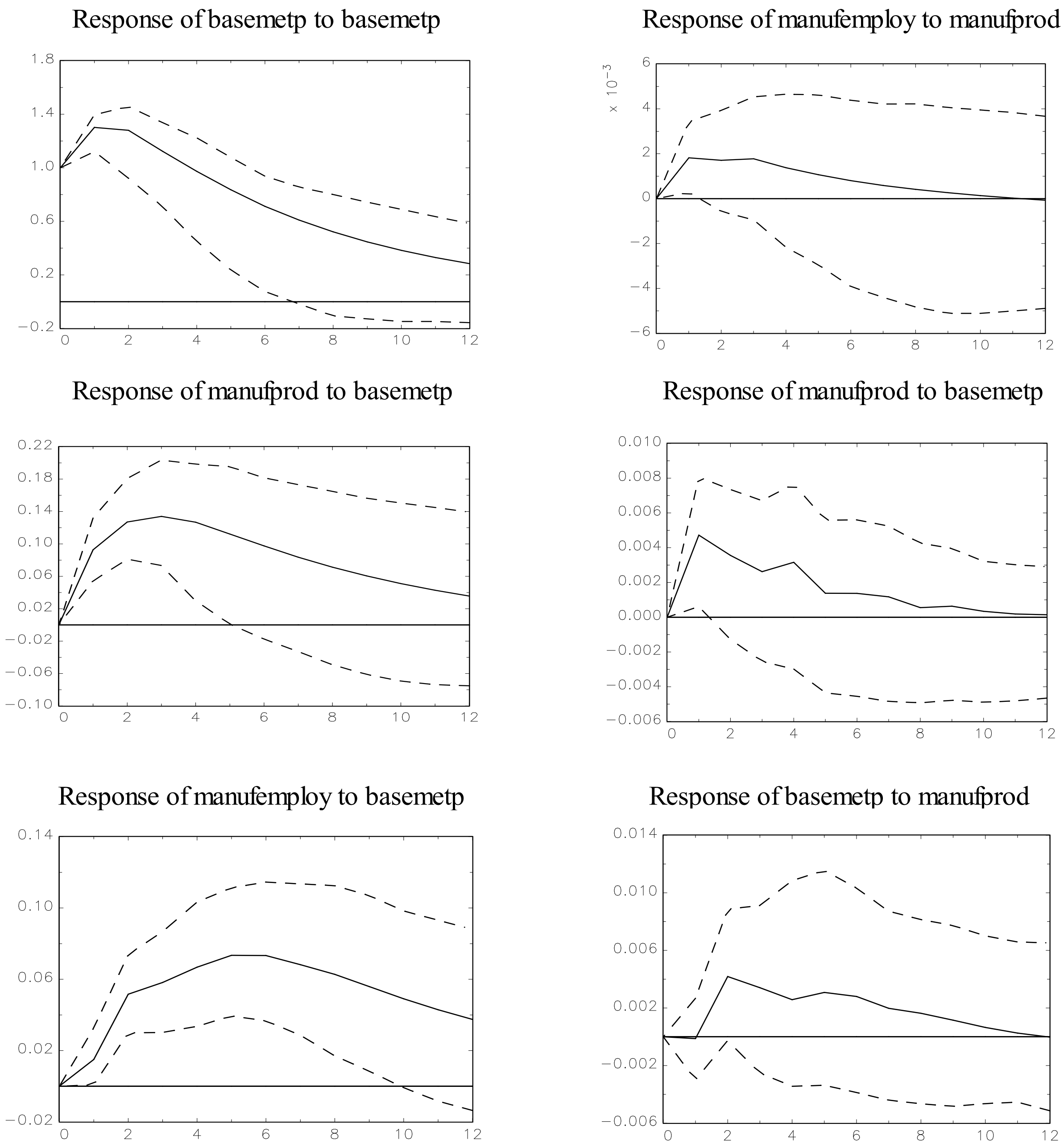
These findings have very important policy implications. The first is that in order for South Africa to take advantage of an increase in commodity prices (commodity boom), the commodity sectors need to be better linked with the other sectors, such as the manufacturing sector. This could be achieved by ensuring that commodities have added value before they are exported. The added value will ensure that production in the mining sector has a positive and significant effect on production and employment in the manufacturing sector. This, in turn, will have a positive effect on production and employment in the other sectors of the economy and help reduce the higher level of unemployment in South Africa.

Figure 2.1 Line plots of the natural logarithm of the series



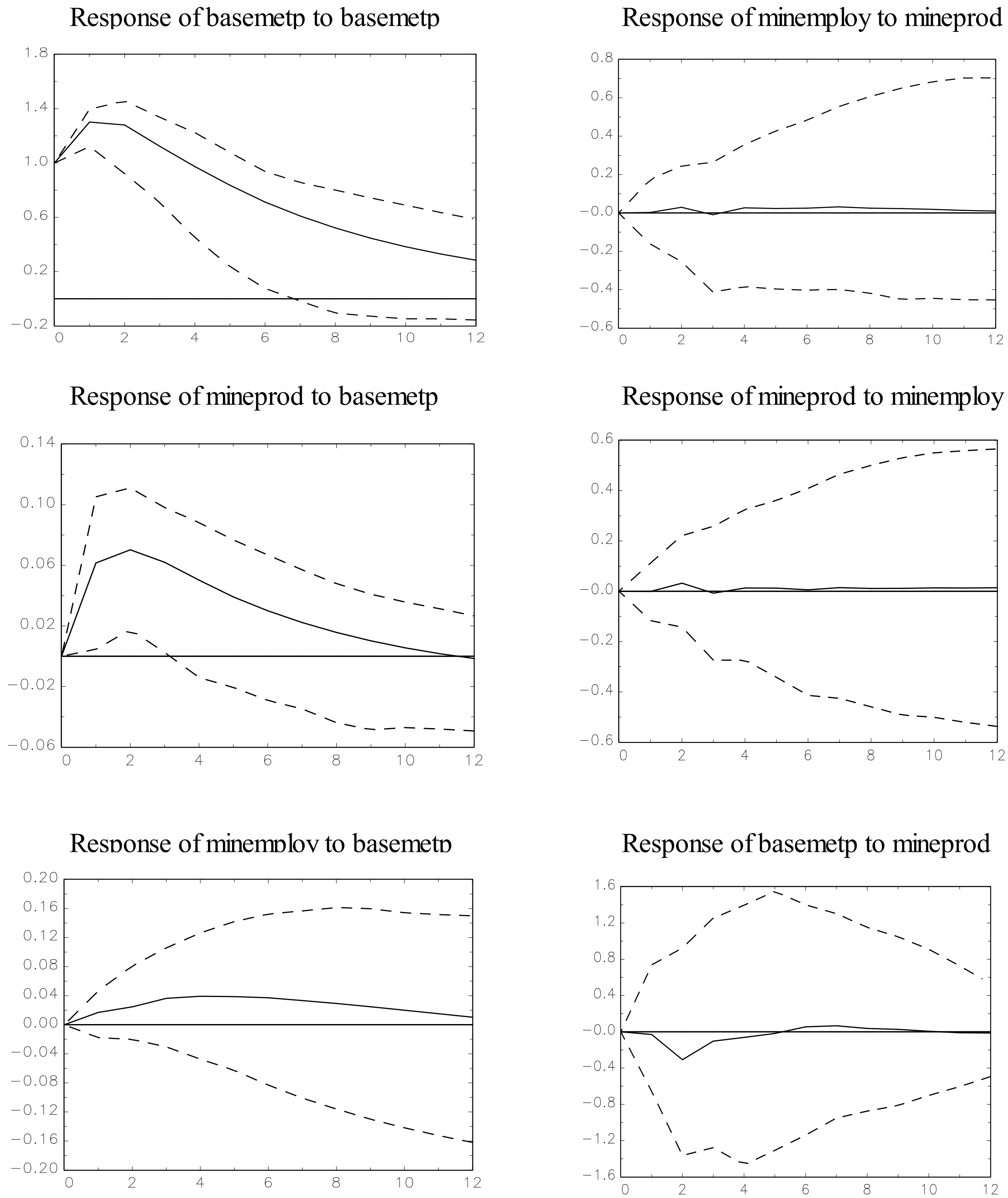
Notes: coalp is the price of coal, manufprod and mineprod are production levels in the manufacturing and mining sectors,: agricp, basemetp, precmetp are agricultural commodities, base metal and precious metal price indices, manufemploy and minemploy are the employment levels in the manufacturing and mining sectors, respectively.

Figure 2.2 Impulse Response Functions-Base metal price index in the manufacturing Sector



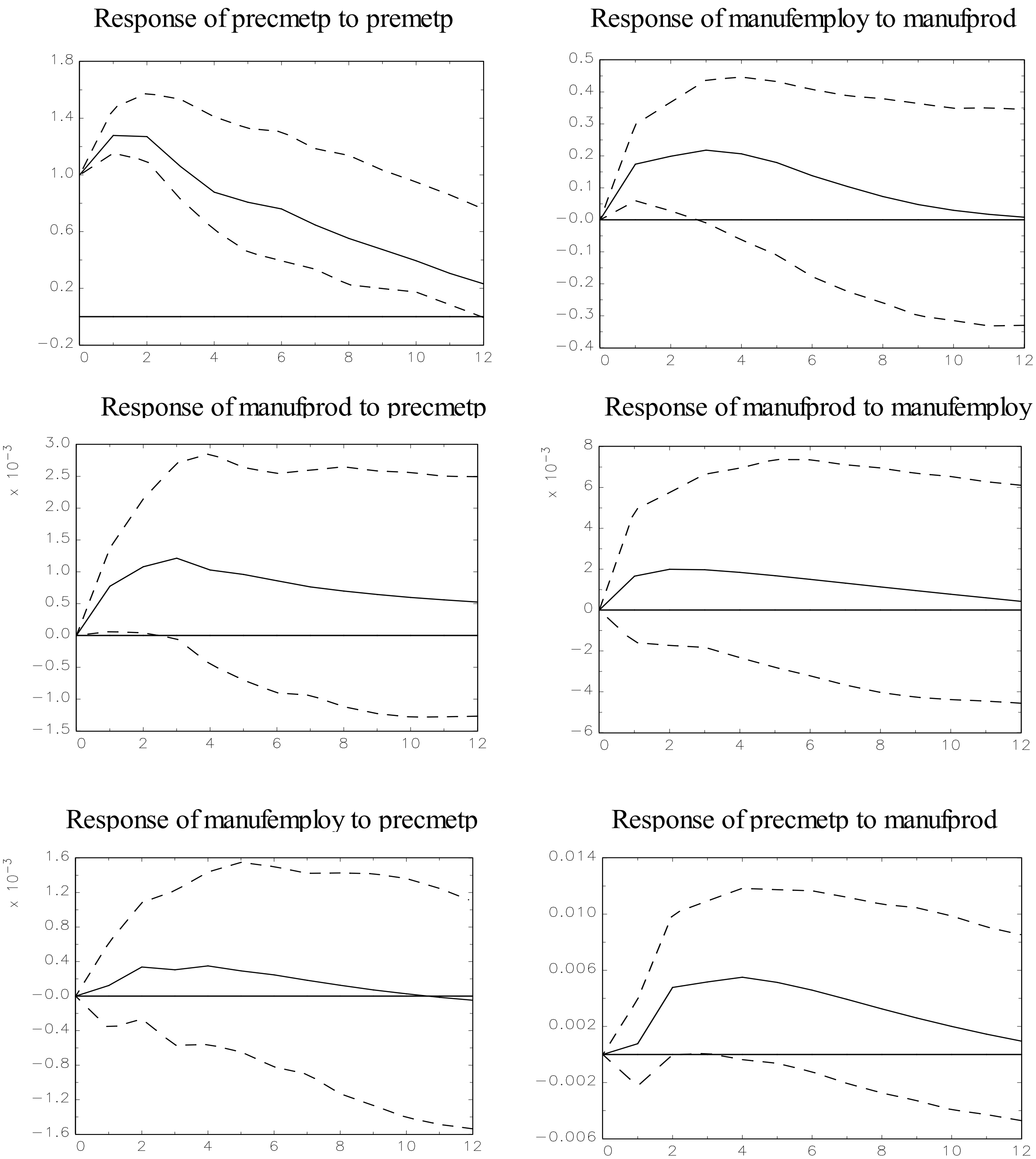
Notes: Cholesky ordering (basemetp, manufprod, manufemploy), basemetp is the base metal price index, manufprod is the production level in the manufacturing sector, and manufemploy is the employment in the manufacturing sector. The vertical axis represents the value of the response variable and the horizontal axis represents the number of periods.

Figure 2.3 Impulse Response Functions-Base metal price index and the mining sector



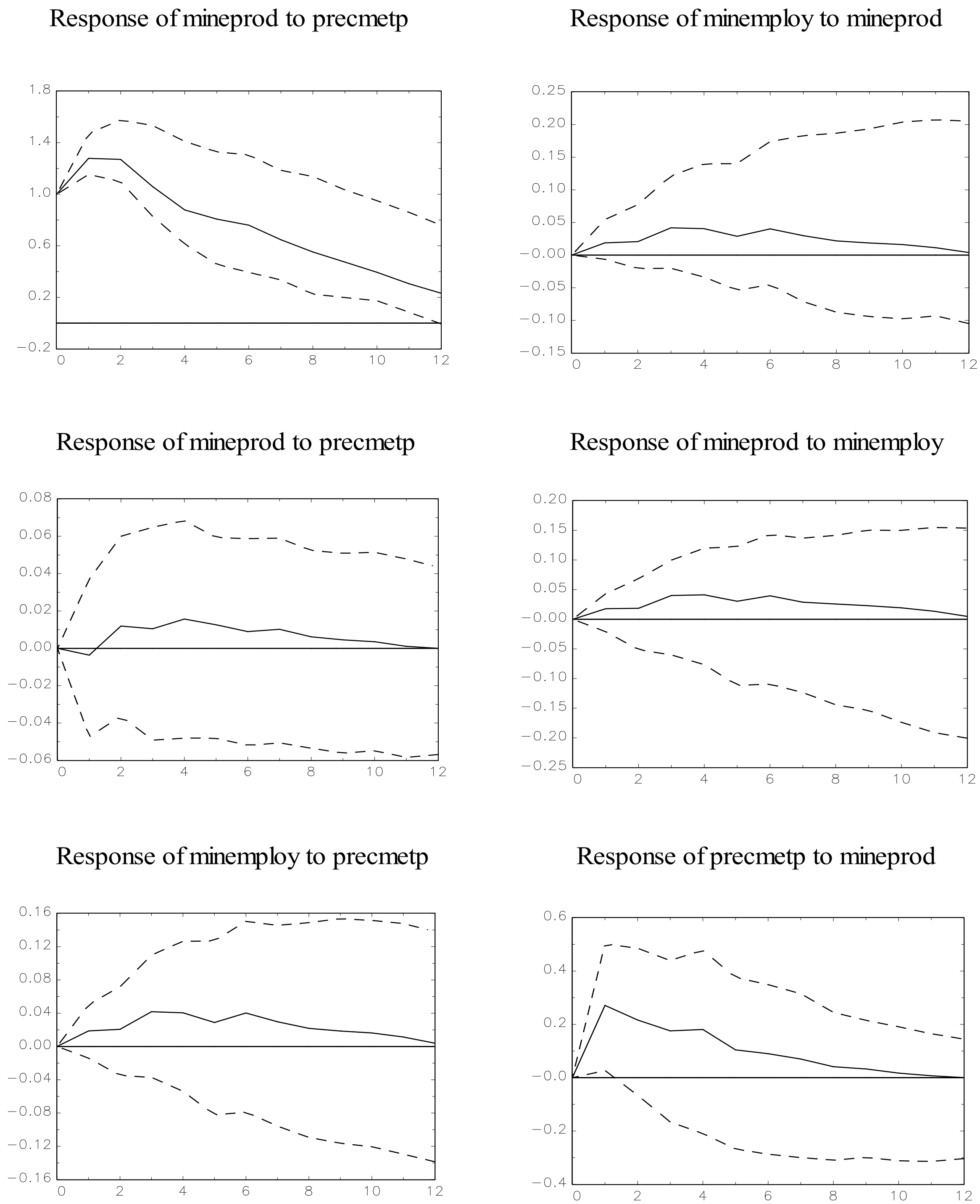
Notes: Cholesky ordering (basemetp, mineprod, minemploy), basemetp is the base metal price index,mineprod is the production level in the mining sector, and minemploy is the employment in the mining sector. The vertical axis represents the value of the response variable and the horizontal axis represents the number of periods.

Figure 2.4 Impulse Response Functions-Precious metal price index and manufacturing sector



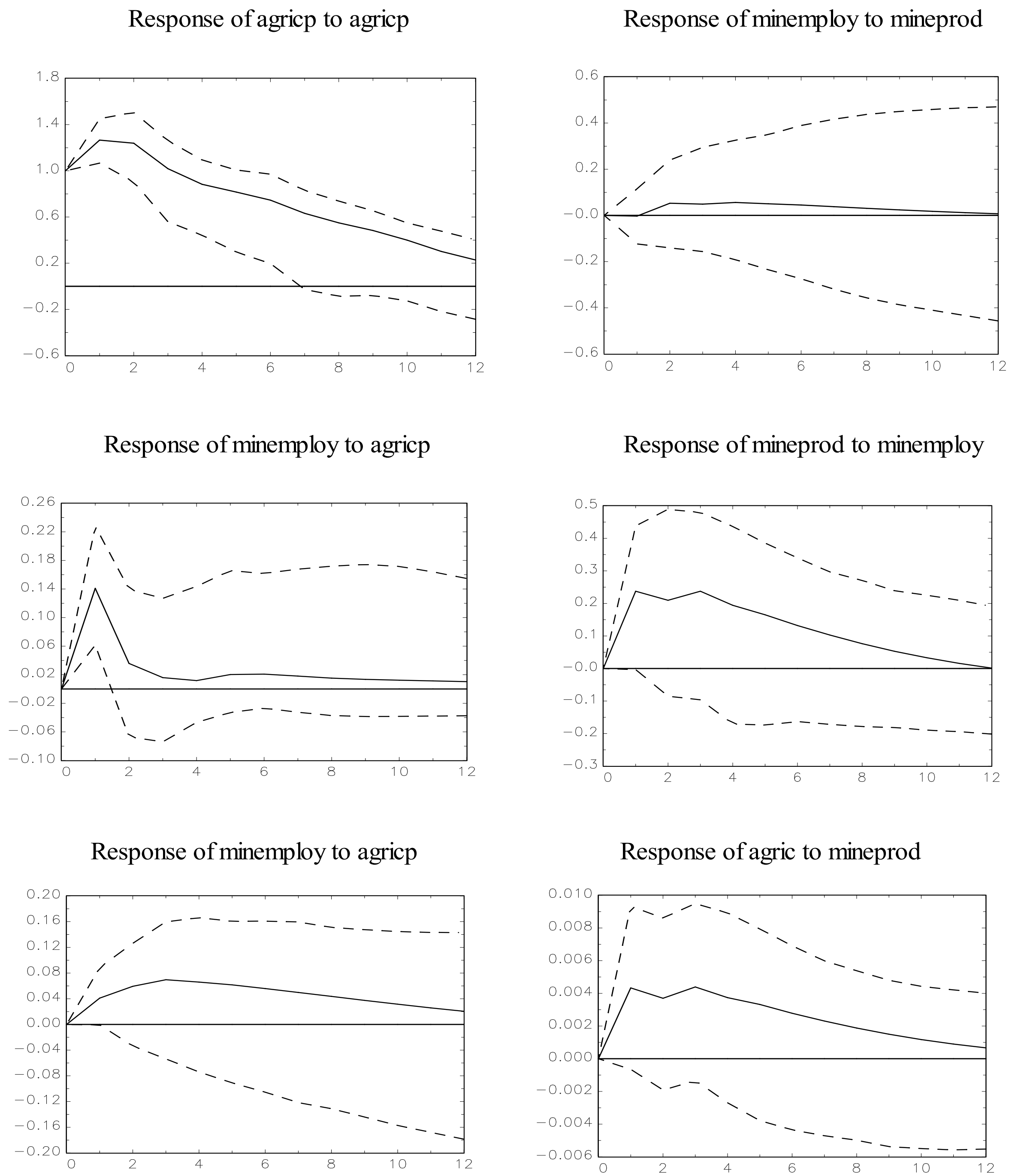
Notes: Cholesky ordering (precmetp, manufprod, manufemploy), precmetp is the precious metal price index, manufprod is the production level in the manufacturing sector, and manufemploy is the employment in the manufacturing sector. The vertical axis represents the value of the response variable and the horizontal axis represents the number of periods.

Figure 2.5 Impulse Response Functions - Precious metal price index and the mining sector



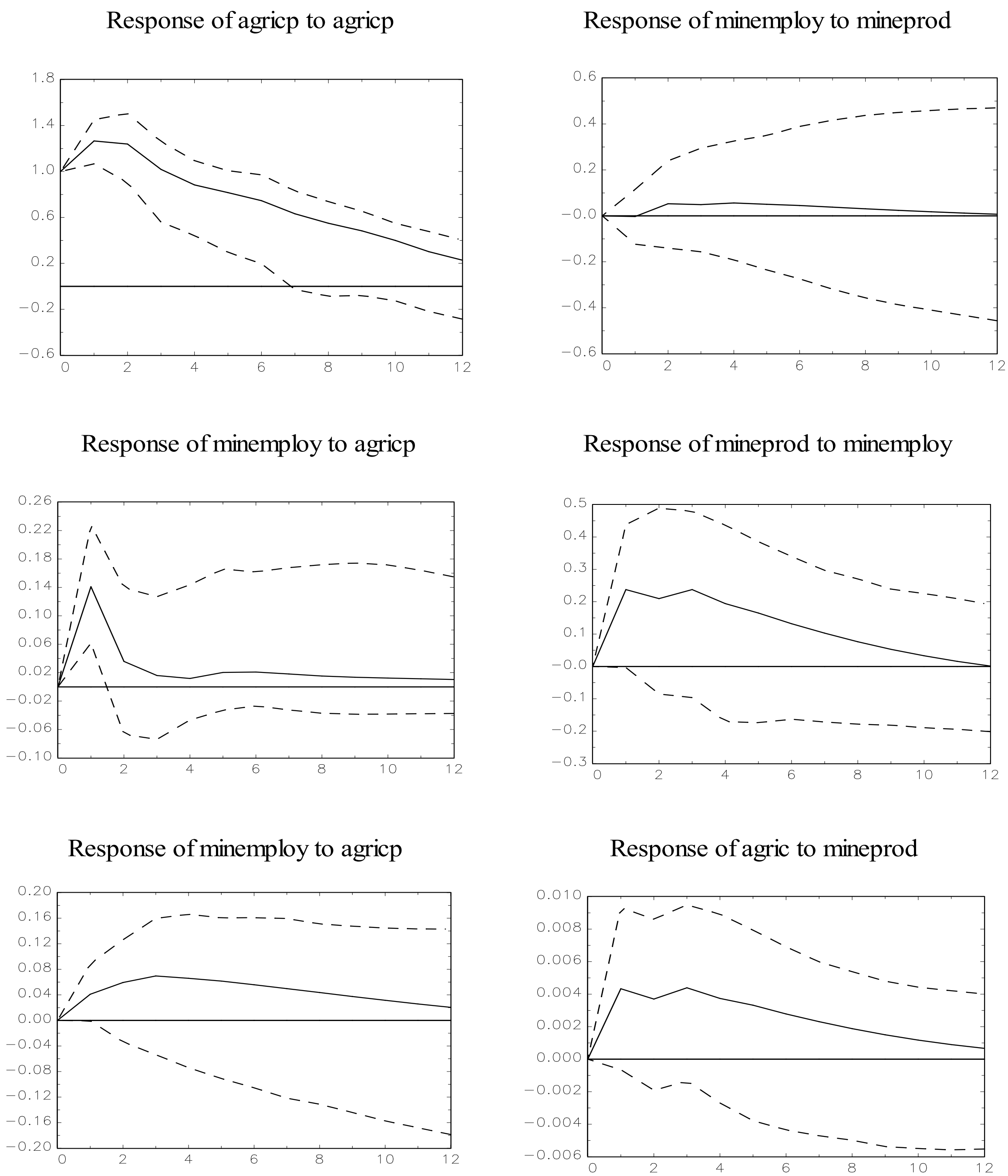
Notes: Cholesky ordering (precmetp, mineprod, minemploy), precmetp is the precious metal price index,mineprod is the production level in the mining sector, and minemploy is the employment in the mining sector. The vertical axis represents the value of the response variable and the horizontal axis represents the number of periods.

Figure 2.6 Impulse Response Functions-Agricultural commodities in manufacturing sector



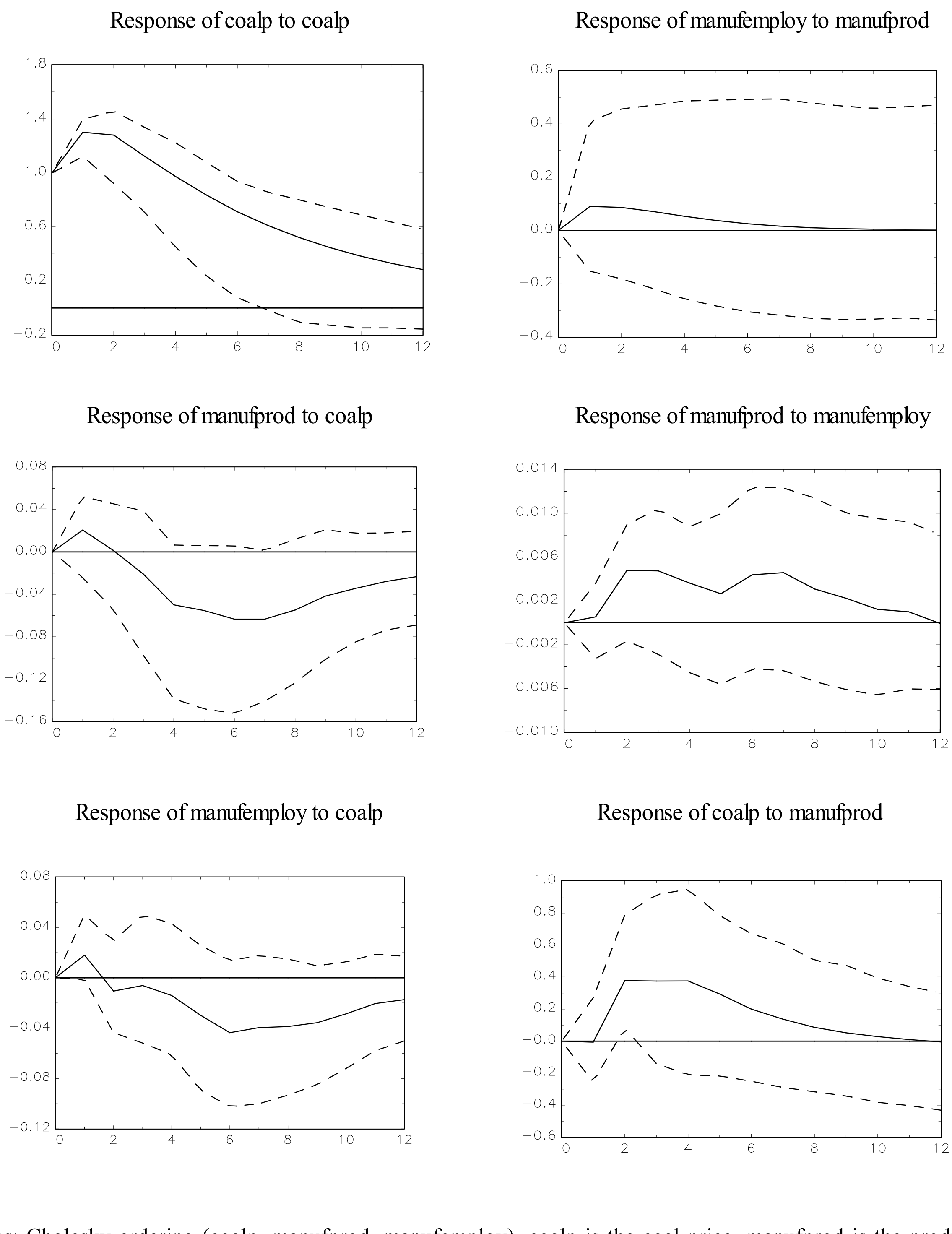
Notes: Cholesky ordering (agricp, manufprod, manufemploy), agricp is the agricultural commodity price index, manufprod is the production level in the manufacturing sector, and manufemploy is the employment in the manufacturing sector.

Figure 2.7 Impulse Response Functions-Agricultural commodities prices in the mining sector



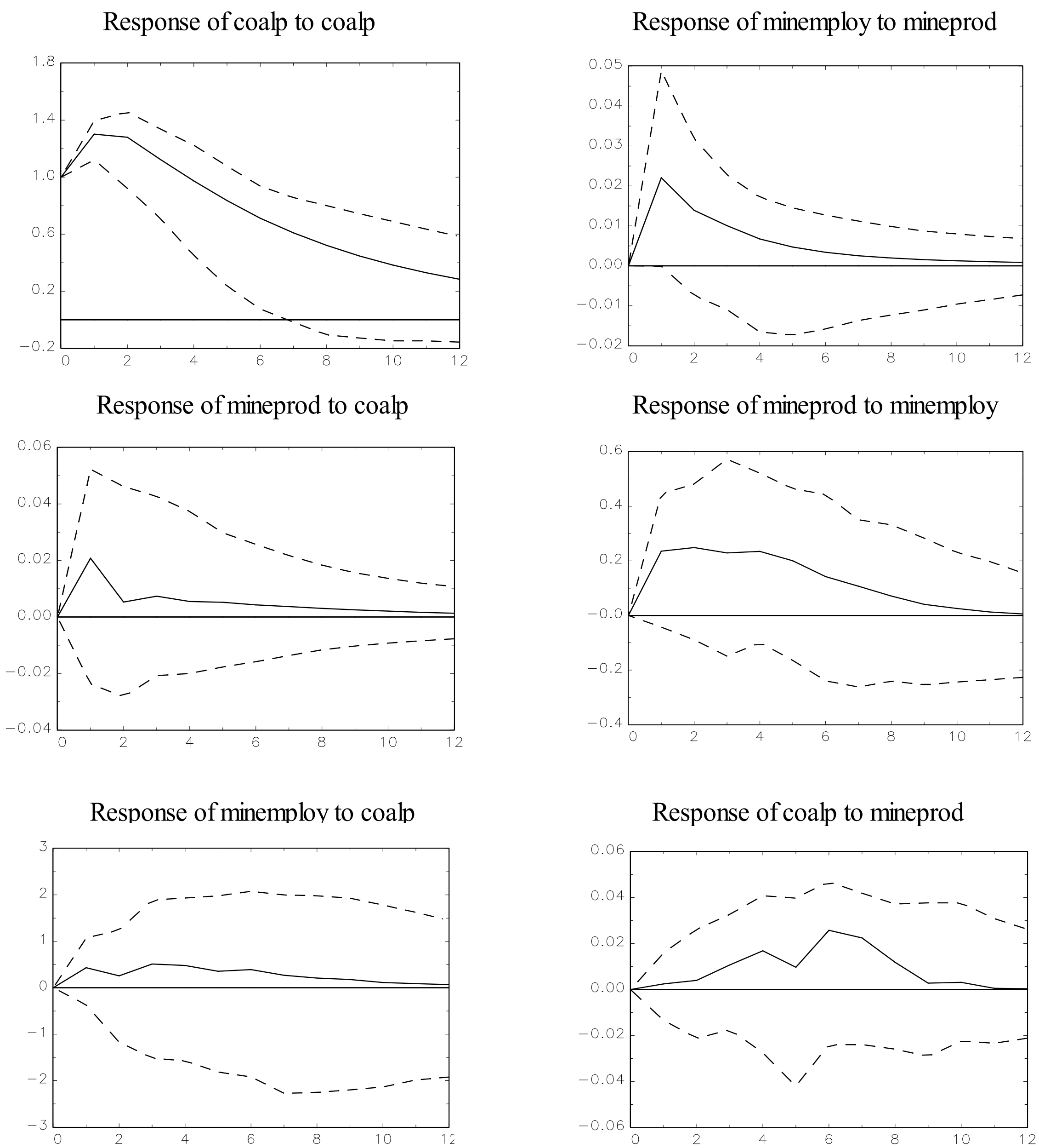
Notes: Cholesky ordering (agricp, mineprod, minemploy), agricp is the agricultural commodity price index,mineprod is the production level in the mining sector, and minemploy is the employment in the mining sector.

Figure 2.8 Impulse Response Functions - Coal price and the manufacturing sector



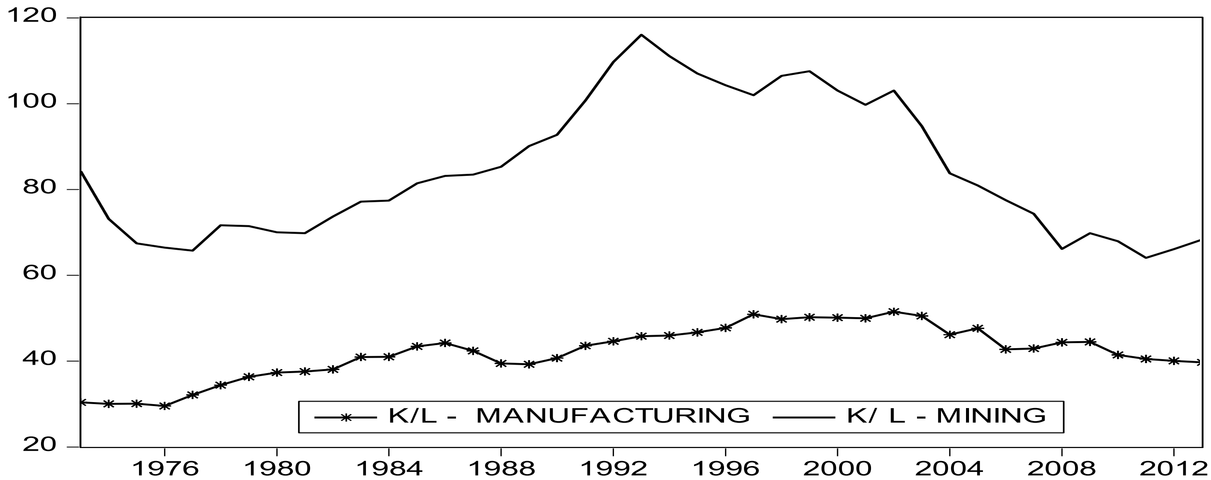
Notes: Cholesky ordering (coalp, manufprod, manufemploy), coalp is the coal price, manufprod is the production level in the manufacturing sector, and manufemploy is the employment in the manufacturing sector.

Figure 2.9 Impulse Response Functions - Coal price and the mining sector



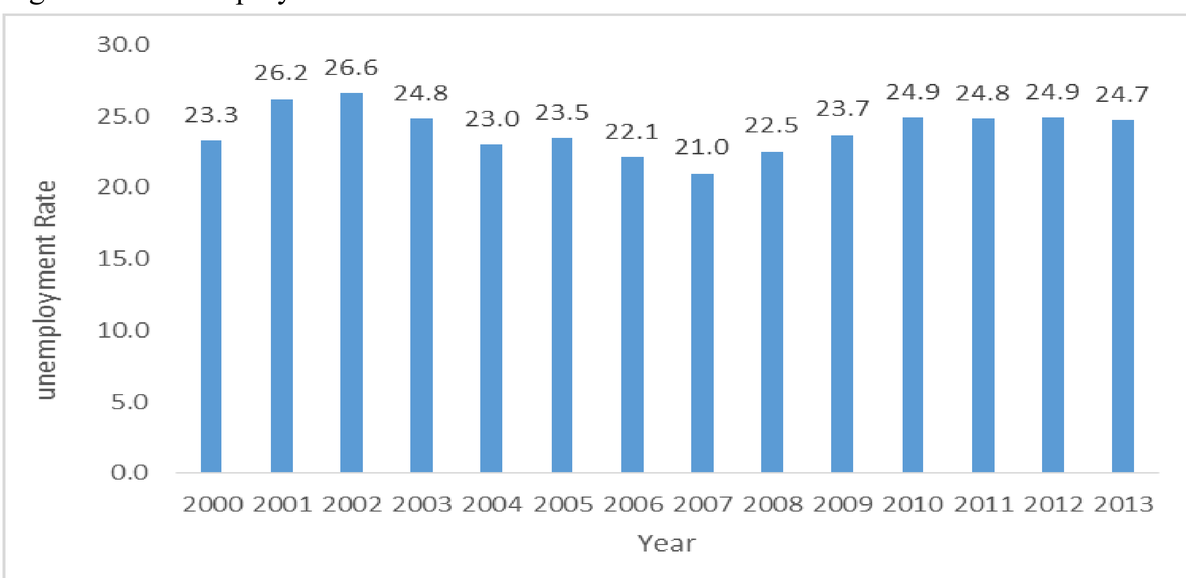
Notes: Cholesky ordering (agricp, mineprod, minemploy), agricp is the agricultural commodity price index, mineprod is the production level in the mining sector, and minemploy is the employment in the mining sector.

Figure 2.10 Capital to labor ratio- mining and manufacturing



Source: South African Reserve Bank.

Figure 2.11 Unemployment Rate in South Africa



Source: IFS - IMF

Table 2.1 Unit Root Test – Augmented Dickey-Fuller Test

	Levels			First Difference		
Variable	Model	Test Statistics	Lags	Model	Test Statistics	Lags
manufemploy	c	-2.048	2	none	-7.142*	1
minemploy	c,t	-2.712	2	c	-5.256*	2
mineprod	c	-2.612	3	none	-5.767*	7
manufprod	c,t	-3.219	2	c	-11.562*	0
basemetp	c,t	-3.101	1	c	-9.103*	0
precmetp	c,t	-2.758	3	c	-5.152*	2
agricp	c,t	-2.773	1	c	-9.370*	0
coalp	c,t	-2.242	5	c	-7.166*	4

Notes: "*" indicates rejection of the null hypothesis, that the series has unit root. The critical values of ADF test for a model with "c,t" are -3.95, -3.41, and -3.13 for 1%, 5%, 10%, respectively. The critical values of ADF test for a model with "c" are -3.43, -2.86, and -2.57 for 1%, 5%, 10%, respectively. The critical values of ADF test for a model with no deterministic term "none" are -2.56, -1.94 and -1.62 for 1%, 5%, 10% significant levels, respectively. The critical values are taken from Davidson, R. and MacKinnon, J. (1993).

Table 2.2 Unit Root Test – Phillip Peron (PP) Test

Variable	Model	Test Stat.	Model	Test Stat.
manufemploy	c	-2.28	none	-11.25*
minemploy	c,t	-1.47	c	-8.83*
mineprod	c	-0.16	none	-18.18*
manufprod	c,t	-3.23	c	-11.63*
basemetp	c,t	-1.46	c	-8.97*
precmetp	c,t	-2.14	c	-11.16*
agricp	c,t	-2.54	c	-9.31*
coalp	c,t	-2.5	c	-10.00*

Notes: "*" indicates rejection of the null hypothesis, that the series has unit root. The critical values for PP test for 1%, 5% and 10% significance levels for model with "c" are -3.43, -2.86, and -2.57; for model with "c,t" are -3.96,-3.41, and -3.13; and for a model with no deterministic trend are -2.56, -1.93, -1.61.

Table 2.3 Cointegration Tes for the Manufacturing Sector

Model 2A: X = (basemetp, manufprod, manufemploy)				
Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
$r \leq 2$	0.22	8.18	0.22	8.18
$r \leq 1$	6.72	17.95	6.50	14.90
$r = 0$	19.50	31.52	12.78	21.07
Model 2B: X = (precmetp, manufprod, manufemploy)				
Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
$r \leq 2$	0.01	8.18	0.01	8.18
$r \leq 1$	7.51	17.59	7.51	14.90
$r = 0$	18.90	31.52	11.40	21.07
Model 2C: X = (agricp, manufprod, manufemploy)				
Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
$r \leq 2$	0.15	8.18	0.2	8.18
$r \leq 1$	4.98	17.59	4.8	14.90
$r = 0$	14.97	31.52	10.0	21.07
Model 2D: X = (coalp, manufprod, manufemploy)				
Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
$r \leq 2$	0.11	8.18	0.11	8.18
$r \leq 1$	7.22	17.59	7.11	14.90
$r = 0$	21.43	31.52	14.21	21.07

Notes: Critical values correspond to 5% significance level.

Table 2.4 Cointegration Test for the Mining Sector

Model 2A: X = (basemetp, mineprod, minemploy)

Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
r ≤ 2	0.98		0.98	8.18
r ≤ 1	5.24		4.27	14.90
r = 0	25.23		19.99	21.07

Model 2B: X = (precmetp, mineprod, minemploy)

Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
r ≤ 2	1.34	8.18	1.34	8.18
r ≤ 1	6.01	17.59	4.67	14.90
r = 0	25.50	31.52	19.52	21.07

Model 2C: X = (agricp, mineprod, minemploy)

Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
r ≤ 2	0.42	8.18	0.40	8.18
r ≤ 1	3.89	17.59	3.47	14.90
r = 0	24.13	31.52	20.24	21.07

Model 2D: X = (coalp, mineprod, minemploy)

Hypothesis	Trace Test		Maximum-Eigenvalue Test	
Null	Test Stat.	Crit. Value	Test Stat.	Crit. Value
r ≤ 2	1.16	8.18	1.16	8.18
r ≤ 1	8.38	17.59	7.21	14.90
r = 0	22.12	31.52	13.75	21.07

Notes: Critical values correspond to 5% significance level.

Table 2.5 Estimated VAR Models

	Manufacturing Sector		Mining Sector	
Model	Deterministic trend	# Lags	Deterministic trend	# Lags
Model A (with basemetp)	c,t	2	c,t	3
Model B (with precmetp)	c,t	4	c,t	3
Model C (with agricp)	c,t	3	c,t	2
Model D (with coalp)	c,t	2	c,t	2

Notes: The optimal lag length was chosen by minimizing the Akaike Information Criteria.

Table 2.6 Model Diagnostic Results

	Manufacturing Sector			Mining Sector		
Model	Portmanteau	LM	Jarque-Berra	Portmanteau	LM	Jarque-Berra
A	0.12	0.81	0.00*	0.71	0.83	0.00*
B	0.24	0.39	0.00*	0.97	0.44	0.00*
C	0.34	0.95	0.00*	0.81	0.63	0.00*
D	0.51	0.32	0.00*	0.18	0.12	0.00*

Notes: “*” indicates rejection at the conventional 5% significance level. The numbers given are probability values.

Table 2.7 Granger-Causality Test for the Manufacturing Sector

Null Hypothesis	F-statistic	p-value
basemetp does not granger cause manufprod	9.8	0.00***
manufprod does not granger cause basemetp	3.75	0.01**
basemetp does not granger cause manufemploy	3.32	0.02**
manufemploy does not granger cause basemetp	1.44	0.23
precmetp does not granger cause manufprod	2.85	0.02**
manufprod does not granger cause precmetp	1.15	0.33
precmetp does not granger cause manufemploy	0.94	0.44
manufemploy does not granger cause precmetp	0.51	0.73
agricp does not granger cause manufprod	4.64	0.01**
manufprod does not granger cause agricp	0.81	0.44
agricp does not granger cause manufemploy	3.42	0.03**
manufemploy does not granger cause agricp	0.99	0.37
coalp does not granger cause manufprod	11.61	0.00***
manufprod does not granger cause coalp	1.58	0.18
coalp does not granger cause manufemploy	3.13	0.02**
manufemploy does not granger cause coalp	0.40	0.81
manufprod does not granger cause manufemploy	4.23	0.01**
manufemploy does not granger cause manufprod	2.16	0.09*

Notes: "***", "**", and "*" indicate rejection of the null at 1%, 5%, and 10% significance level, respectively. Optimal number of lags selected using the AIC

Table 2.8 Granger-Causality Test for the Mining Sector

Null Hypothesis	F-statistic	p-value
basemetp does not granger cause mineprod	6.4	0.00***
mineprod does not granger cause basemetp	0.28	0.76
basemetp does not granger cause minemploy	3.27	0.01**
minemploy does not granger cause basemetp	1.06	0.35
precmetp does not granger cause mineprod	2.31	0.06*
mineprod does not granger cause precmetp	3.84	0.05*
precmetp does not granger cause minemploy	2.13	0.09*
minemploy does not granger cause precmetp	0.87	0.46
agricp does not granger cause mineprod	4.73	0.00***
mineprod does not granger cause agricp	0.81	0.49
agricp does not granger cause minemploy	1.22	0.30
minemploy does not granger cause agricp	1.31	0.27
coalp does not granger cause mineprod	3.31	0.01**
mineprod does not granger cause coalp	1.04	0.39
coalp does not granger cause minemploy	2.81	0.09*
minemploy does not granger cause coalp	0.53	0.47
mineprod does not granger cause minemploy	3.10	0.08*
minemploy does not granger cause mineprod	3.83	0.02**

Notes: "****", "**" and "*" indicate rejection of the null at 1%, 5% and 10% significance level, respectively. The optimal number of lags was chosen based on Akaike Information Criteria.

Table 2.9 Forecast Error Variance Decomposition for model A - manufacturing sector

Variance Decomposition of base metal prices (basemetp)			
Period	basemetp	manufprod	manufemploy
1	100.00	0.00	0.00
4	99.60	0.40	0.01
8	98.69	0.44	0.86
12	96.38	0.43	3.19
Variance Decomposition of industrial production (manufprod)			
Period	basemetp	manufprod	manufemploy
1	2.87	97.13	0.00
4	27.69	71.59	0.72
8	32.77	66.63	0.60
12	31.58	67.62	0.80
Variance Decomposition of employment (manufemploy)			
Period	basemetp	manufprod	manufemploy
1	2.89	0.53	96.58
4	12.85	4.08	83.07
8	17.30	2.89	79.81
12	17.23	2.24	80.52

Notes: basemetp is the base metal price index, prodmanuf and employmanuf are the industrial production and employment for the manufacturing sector, respectively. The VAR uses the following Cholesky ordering: (basemetp,prodmanuf, employmanuf).

Table 2.10Forecast Error Variance Decomposition for model B - manufacturing sector

Variance Decomposition of preciouis metal prices (precmetp)			
Period	precmetp	manufprod	manufemploy
1	100.0	0.00	0.00
4	98.50	1.25	0.25
8	95.84	3.04	1.12
12	93.61	4.19	2.20
Variance Decomposition of industrial production (manufprod)			
Period	precmetp	manufprod	manufemploy
1	0.26	99.74	0.00
4	3.67	96.03	0.30
8	3.73	95.75	0.52
12	3.76	95.58	0.66
Variance Decomposition of employment (precmetp)			
Period	precmetp	manufprod	manufemploy
1	0.00	2.20	97.80
4	0.17	15.32	84.50
8	0.18	18.93	80.89
12	0.86	20.23	78.91

Notes: precmetp is the base metal price index, prodmanuf and employmanuf are the industrial production and employment for the manufacturing sector, respectively. The VAR uses the following Cholesky ordering: (precmetp,prodmanuf, employmanuf).

Table 2.11 Forecast Error Variance Decomposition for model C - manufacturing sector

Variance Decomposition of agricultural commodity prices (agricp)			
Period	agricp	manufprod	manufemploy
1	100.0	0.00	0.00
4	99.8	0.09	0.07
8	99.34	0.14	0.52
12	98.44	0.19	1.37
Variance Decomposition of industrial production (manufprod)			
Period	agricp	manufprod	manufemploy
1	2.13	97.87	0.00
4	13.58	86.37	0.06
8	17.11	82.71	0.19
12	17.96	81.29	0.75
Variance Decomposition of employment (manufemploy)			
Period	agricp	manufprod	manufemploy
1	0.10	1.85	98.05
4	3.68	9.34	86.98
8	5.04	8.62	86.34
12	4.98	7.35	87.67

Notes: agricp is the agricultural commodity price index, manufprod and manufemploy are the industrial production and employment for the manufacturing sector, respectively. Cholesky ordering is: (agricp,manufprod, manufemploy).

Table 2.12 Forecast Error Variance Decomposition for model D - manufacturing sector

Variance Decomposition of coal prices (coalp)			
Period	coalp	manufprod	manufemploy
1	100.0	0.00	0.00
4	96.30	3.50	0.20
8	93.24	6.42	0.35
12	91.49	8.20	0.31
Variance Decomposition of industrial production (manufprod)			
Period	coalp	manufprod	manufemploy
1	6.26	93.74	0.00
4	6.47	91.92	1.61
8	4.13	94.02	1.84
12	3.19	95.43	1.38
Variance Decomposition of employment (manufemploy)			
Period	coalp	manufprod	manufemploy
1	1.84	0.46	97.70
4	3.30	8.15	88.55
8	1.69	8.55	89.77
12	1.28	7.48	91.24

Notes: coalp is the coal price, manufprod and manufemploy are the industrial production and employment for the manufacturing sector, respectively. The VAR uses the following Cholesky ordering: (coalp, manufprod, minemploy).

Table 2.13 Forecast Variance Error Decomposition for model A - Mining Sector

Variance Decomposition of base metal prices (basemetp)			
Period	basemetp	mineprod	minemploy
1	100.0	0.00	0.00
4	99.79	0.11	0.10
8	99.78	0.15	0.07
12	99.64	0.17	0.19
Variance Decomposition of industrial production (mineprod)			
Period	basemetp	mineprod	minemploy
1	0.84	99.16	0.00
4	13.08	84.00	2.92
8	14.80	81.62	3.58
12	14.39	82.11	3.50
Variance Decomposition of employment (minemploy)			
Period	basemetp	mineprod	minemploy
1	2.76	1.46	95.78
4	6.17	2.03	91.81
8	7.04	2.29	90.67
12	6.79	2.40	90.81

Notes: basemetp is the base metal price index, prodmine and employmine are the industrial production and employment for the mining sector, respectively. The VAR uses the following Cholesky ordering: (basemetp, mineprod, minemploy).

Table 2.14 Forecast Error Variance Decomposition for model B - mining sector

Variance Decomposition of precious metal prices (precmetp)			
Period	precmetp	mineprod	minemploy
1	100.0	0.00	0.00
4	94.36	5.48	0.16
8	86.39	13.41	0.20
12	84.72	15.02	0.26
Variance Decomposition of industrial production (mineprod)			
Period	precmetp	mineprod	employnine
1	2.68	97.32	0.00
4	2.81	93.37	3.83
8	6.80	85.69	7.51
12	7.03	84.38	4.54
Variance Decomposition of employment (minemploy)			
Period	precmetp	mineprod	minemploy
1	0.51	3.61	95.88
4	4.61	5.05	90.34
8	5.44	6.45	88.11
12	5.69	7.46	86.85

Notes: precmetp is the base metal price index, mineprod and minemploy are the industrial production and employment for the mining sector, respectively. The VAR uses the following Cholesky ordering: (precmetp, mineprod, minemploy).

Table 2.15 Forecast Error Variance Decomposition for model C - mining sector

Variance Decomposition of agricultural commodity prices (agricp)			
Period	agricp	mineprod	minemploy
1	100.0	0.00	0.00
4	99.5	0.49	0.01
8	99.19	0.31	0.50
12	97.39	0.26	2.35
Variance Decomposition of industrial production (mineprod)			
Period	agricp	mineprod	minemploy
1	0.10	99.90	0.00
4	4.82	94.81	0.37
8	4.15	92.39	3.46
12	3.99	86.99	9.02
Variance Decomposition of employment (minemploy)			
Period	agricp	mineprod	minemploy
1	0.15	0.10	99.75
4	2.83	0.21	96.96
8	2.79	0.12	97.09
12	2.10	0.17	97.73

Notes: agricp is the agricultural commodity price index, mineprod and minemploy are the industrial production and employment for the mining sector, respectively. The VAR uses the following Cholesky ordering: (agricp, mineprod, minemploy)

Table 2.16 Forecast Error Variance Decomposition for model D - mining sector

Variance Decomposition of coal prices (coalp)			
Period	coalp	mineprod	minemploy
1	100.0	0.00	0.00
4	99.02	0.24	0.73
8	98.16	0.46	1.38
12	98.07	0.62	1.30
Variance Decomposition of industrial production (mineprod)			
Period	coalp	mineprod	minemploy
1	0.23	99.77	0.00
4	1.41	94.00	4.58
8	1.27	92.85	5.88
12	1.21	92.92	5.87
Variance Decomposition of employment (minemploy)			
Period	coalp	mineprod	minemploy
1	2.28	1.92	95.80
4	5.97	2.94	91.09
8	6.62	3.43	89.96
12	6.80	3.58	89.62

Notes: coalp is the coal price, mineprod and minemploy are the industrial production and employment for the mining sector, respectively. The VAR uses the following Cholesky ordering: (coalp, prodmanuf, employmanuf).

Chapter 3 - Volatility Transmission Between Commodity Prices and The Nominal Exchange Rate in South Africa

3.1 Introduction

The volatility of an asset's price is an indication of the risk of holding the asset. The analysis of asset price volatilities and the interdependence of such volatilities are of great importance to investors, researchers, and policy makers. From an investor's standpoint, knowing the volatilities of different assets might enhance risk management as well as portfolio optimization. In the last 15 years or so, there has been a marked increase in commodity prices, which has revived the debate on the impact of such a price surge on economic activity. African economies are highly dependent on commodities. Despite its higher level of industrialization compared to other countries on the continent, the South African economy is also highly dependent on commodity prices not only for imports but also exports and income. This higher dependence on commodities implies that commodity price fluctuations are bound to have significant effects on macroeconomic variables. The South African currency is so influenced by commodity prices that it is labeled as "commodity currency", Chen et al. (2010). As the left panel of figure 1 shows, both the commodity prices and the exchange rate have experienced more frequent periods of fluctuation since late 1999.

This correlation between commodity prices and the exchange rate of commodity rich countries has been documented in earlier studies[34]. So, the fluctuations in commodity prices that are accompanied by similar fluctuations in exchange rate have researchers and policy makers asking how much of the volatility in commodity prices are transmitted to exchange rate volatility.

Although there are a growing number of empirical studies examining the link between commodity prices and exchange rate in the literature, most of the existing studies examine the co-movement between commodity prices and exchange rate and not their volatilities. A larger numbers of these studies focus on a single commodity, mainly oil or gold, and almost none analyze other commodities. Moreover, our literature review indicates that there virtually no studies analyzing the volatility transmission between commodity prices and the South African exchange rate, despite the fact that South Africa is a world leading producer and exporter of a vast number of commodities.

[34] See for instance Cashin et al. (2003), Tse and Zhao (2011), Arezki et al. (2012) and Beutler (2012).

Motivated by the recent commodity price boom and the scant attention that the impact of commodity price volatility on exchange rate has received, this study analyses the dynamics of volatility transmission from a number of commodities to the nominal exchange rate in South Africa during the period January 1991 June 2014. In particular, we analyze volatility spillovers from the price of gold, platinum, oil, palladium, and silver to the volatilities in the nominal exchange rate. The contribution of this paper is that it uses both parametric and non-parametric methodologies for the volatility estimation.

For the parametric volatility approach, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is used to estimate the conditional volatilities of the return series. For the non-parametric approach, the realized volatility method is used to estimate the monthly volatility series from the daily return series. Once the volatility series are estimated, two econometric methods are employed to analyze the volatility transmission from commodity prices to the South African exchange rate. In the first approach, we estimate 5 bivariate Vector Autoregressive (VAR) models between the exchange rate volatility and the volatility of each commodity price and carry out a Granger causality analysis. In the second method, we run a linear regression of the exchange rate volatility on the volatilities of the commodity prices using Ordinary Least Squares (OLS) techniques. The Granger causality results indicate that volatility in prices of each of the commodities Granger causes volatility in the nominal exchange rate. The OLS results support the Granger causality results and indicate that volatility in the South African Rand is significantly explained by volatilities in commodity prices.

The rest of the chapter is organized as follows: section 2 presents the literature review; section 3 is a discussion of the methodology and variable definitions; section 4 describes the data analysis and results; and section 5 presents the conclusions and policy recommendations.

3.2 Literature Review

Edwards (1985) develops a model that analyzes the interaction between changes in commodity export prices, money creation, inflation, and the real exchange rate in a developing country. He tests the model using data for Colombia and finds, among other things, that coffee price changes have been negatively related to the rate of devaluation of the crawling peg.

Amano et al. (1998), using time series techniques, find a long run equilibrium relationship between the real domestic price of oil and the real effective exchange rates in Germany, Japan, and the United States. Chen and Rugoff (2003), using data from three commodity rich countries, Australia, Canada, and New Zealand, carry out an empirical re-examination of the exchange rate puzzle[35]. For Australia and New Zealand, they find that the U.S. dollar price of their commodity exports has a strong and stable influence on their floating real rates. However, they also find that after controlling for commodity price shocks, there is still a "Purchase Power Parity" puzzle in the residual.

Cashin et al. (2003) determine how many commodity-exporting countries have 'commodity currencies'. They construct monthly indices of national commodity export prices for 58 commodity-exporting countries between 1980 and 2002. Their results indicate the existence of a long-run relationship between national real exchange rate and real commodity prices for about one third of the commodity-exporting countries.

Chen et al. (2010), using quarterly data, find that currency exchange rates of commodity exporting countries have a strong forecasting ability for the spot prices of the commodities they export.

Muhammad et al. (2011) use daily data from 2007 to 2010, GARCH, and EGARCH models to examine the impact of oil price changes on the nominal exchange rate. Their results show that a rise in oil prices leads to a depreciation of the Nigerian Naira vis-à-vis the US dollar. Apergis and Papoulakos (2013) use a Vector Error Correction Model (VECM), as well as a GARCH model, to explore the association between gold and the Australian dollar. Their findings indicate that there is relationship between the exchange rate and gold prices, in terms of both means and conditional volatilities.

The current study contributes to the literature by analyzing the volatility transmission from prices of five different commodities and the nominal exchange rate in a resource rich country, South Africa. Moreover, we employ conditional and realized volatility techniques to estimate commodity prices and exchange rate volatility, and then apply time series techniques to analyze the volatility transmission from commodity prices to the South African nominal exchange rate.

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[35] These are behaviors in exchange rates that are not explained and challenge the existing theories. These include "forward bias" puzzle, "purchase power parity" puzzle and "exchange rate disconnect" puzzle. For a more detailed analyze on exchange rate puzzle refer to Fama (1984), Frankel and Rose (1994), and Obstfeld and Rugoff (2000).

3.3 Analytical Framework

3.3.1 Model Specification

This paper analyses the volatility transmission between commodity prices and the nominal exchange rate in South Africa. The paper follows Aziz (2009) and Kin and Courage (2014) to estimate the relationship between commodity prices and exchange rates. Both Aziz (2009) and Kin and Courage (2014) modeled the exchange rate as a function of oil price and interest rate. This research modifies the model by modeling the volatility in exchange rate as a function of the volatility of five commodity prices: gold, platinum, palladium, oil, and silver. The model can be expressed as:

$$retexrate = f(rergoldp, retplatp, retoilp, retpalladp, retsilvp) \tag{3.1}$$

where the exchange rate volatility (retexrate) is a function of the volatility gold prices (retgoldp), platinum prices (retplatp), oil prices (retoilp), palladium prices (retpalladp) and silver prices (retsilvp).

3.3.2. Methodology

3.3.2.1 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model

The ARCH model was introduced by Engle (1982), and it has become the most widely used model in time series analysis of financial data. These data exhibit temporal dependency in their second order moments and a distribution characterized by fat tails. This makes the hypothesis test statistics and confidence intervals from linear structural models, such as Ordinary Least Squares, inconsistent.

An ARCH process consists of two equations, the conditional mean and the conditional variance equation, that must be estimated simultaneously using interactive maximum likelihood techniques, such as the Marquardt or BHHH algorithms. Given an asset with an expected return of r_t, and the information set available at time t-1, and the conditional variance of h_t, the ARCH(q) process can be expressed by

$$rt \mid Ft{-}1 \sim N(x_t'\beta, h_t^2) = x_t'\beta + \varepsilon t \varepsilon t = h_t Z_t \tag{3.2}$$

$$ht = \alpha 0 + \alpha 1\varepsilon_{t-1}^{2} + \alpha 2\varepsilon_{t-2}^{2} + \ldots + \alpha q\varepsilon_{t-q}^{2} \qquad (3.3)$$

where equations 3.2 and 3.3 are the conditional mean and conditional variance, respectively. The mean equation, x_t' may include lagged values of r_t or exogenous variables, and Z_t is a sequence of independent and identically distributed random variables with mean zero and unit variance. However, the ARCH representation of volatility has some drawbacks in that it requires the inclusion of many parameters, since a high order of ARCH term q has to be estimated in order to capture the dynamics of the conditional variance. To address this and other limitations, Bollerslev (1986) extended the ARCH(q) to a Generalized Autoregressive Conditional Heteroskedasticity, GARCH(p,q) model, where the conditional variance does not only depend on the squares of past residuals, but also on the past conditional variances, such that

$$\mathrm{h_t} = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i h_{t-i}. \qquad (3.4)$$

where $\omega > 0, \alpha_i, \alpha_i \geq 0$, and $\gamma_i \geq 0$. Also, to ensure stability of the model, the GARCH process has to satisfy the following condition:

$$\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \gamma_i < 1$$

The simplest and most widely used GARCH model is the GARCH (1, 1), which can be expressed as

$$r_t = \beta_0 + \beta_1 r_{t-1} + \varepsilon_t \qquad (3.5)$$

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1} \qquad (3.6)$$

where equations 3.5, and 3.6 are the mean and variance equations, respectively, $\omega > 0$, $\alpha_1 \geq 0$ and $\alpha_1 \geq 0$. In this case, the stationarity condition requires that $\alpha_1 + \gamma_1 < 1$. If $\alpha_1 + \gamma_1$ is close to one, then a shock in period t will have a persistent impact.

Before estimating a GARCH type model, the researcher needs to make sure that the use of such a model is justified. One way to determine if a GARCH model is justified is by inspecting plots of the return series and infer if the series exhibit certain characteristics, such as volatility clustering or ARCH effects. A more formal analysis, however, consists of carrying out econometric tests. The most popular econometric test used in the literature to determine the appropriateness of the GARCH model is the ARCH Lagrange Multiplier (LM) test. The test, which was originally proposed by Engle (1982), follows a specific procedure. Given the return of the asset r_t, one estimates the following AR(1) model,

$r_t = \beta_0 + \beta_1 r_{t-1} + \varepsilon_t$

Using the predicted residuals obtained from the above model, one estimates the following ARCH(q) process.

$$\varepsilon_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 \qquad (3.7)$$

The null hypothesis is

H_0: $\alpha_1 = \alpha_2 = \ldots = \alpha_q = 0$, or that there are no ARCH effects in the residuals. The alternative hypothesis is that at least one of the α_is is different from zero. The test statistic, the LM test, is equal to TxR^2 and has a chi-square distribution. If the value of the LM test is greater than the critical value, then the null hypothesis is rejected, implying that there are ARCH effects in the residuals in the model.

3.3.2.2 Realized Volatility Model

Despite the popularity and success of GARCH models capturing the salient features of conditional volatility and different aspects of the data, the parametric volatility models to which the GARCH models belong have some drawbacks. One such drawback with the GARCH approach in estimating volatility is that convergence of the Maximum likelihood estimation process may not be achieved. In addition, there are several different potential GARCH specifications designed to capture different aspects of the data. The multiple specifications allow different researchers to use different specifications in testing for spillovers, making the comparison of different research results difficult. Another[36] issue regarding the use of GARCH volatility models is that under the GARCH approach the volatilities are constructed from past values, meaning that volatility itself is basically unobserved (McMillan and Speight, 2010).

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[36] For more drawbacks of using GARCH models see Andersen et al. (2001) and Kang et al. (2010).

To avoid the limitations of the GARCH models, Andersen et al. (2001) among others, propose a non-parametric volatility model, known as a realized volatility model. Unlike the GARCH model, where volatilities are constructed from past values, the realized volatility approach allows the volatility to be regarded as observed variables (McMillan, et al., 2010).

Suppose that the natural logarithm of an asset's price, p_t, can be represented by

$$d\log\left(p_t\right) = \mu_t d_t + \sigma_t d\varphi_t \tag{3.8}$$

where μ_t, σ_t and φ_t are a predictable drift term, the volatility, and the standard Brownian Motion, respectively. It can be shown that the continuously compounded price change, r_t, can be expressed as;

$$r_t = \log\left(p_t\right) - \log\left(p_{t-1}\right) = \int_{t-1}^{t} \mu_u d_u + \int_{t-1}^{t} \sigma_u d\varphi_u \tag{3.9}$$

It can be shown further that given the information set F_{t-1}, the expected value of r_t can be written as;

$$E\left\{r_t \mid F_{t-1}\right\} = \int_{t-1}^{t} \mu_u du \tag{3.10}$$

By the same token the conditional variance, or Integrated Volatility, can be written as

$$Var\left\{r_t \mid F_{t-1}\right\} \equiv IV = \int_{t-1}^{t} \sigma_u^2 du \tag{3.11}$$

For an appropriate sampling frequency[37], equation 3.11 gives the Realized variance, and its square root is known as the realized volatility, RV. In this study, we use daily return series to compute monthly realized volatility. Following Andersen et al. (2001), we use the following calculation for the annualized monthly realized volatility.

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[37] Andersen et al. (2001) suggest using data with daily frequency or higher.

$$RV = \frac{1}{N}\sum_{i=1}^{N}(r_i - \bar{r})^2 \qquad (3.12)$$

where r_i is the daily return, and N is the number of trading days in a month. Once the realized volatility is computed, the volatility transmission between the commodity prices and nominal exchange rate is analyzed by means of Ordinary Least Squares (OLS) and Vector Autoregressive (VAR) techniques.

3.3.2.3 Ordinary Least Squares

Consider the multiple regression model given in matrix form.

$$y = X\beta + u \qquad (3.13)$$

where y is an $nx1$ column vector of observations of the dependent variables, $X$is a matrix of nxk observations of the explanatory variables, β is a $\kappa x1$ vector of parameters to be estimated, and u is an $nx1$ column vector of residuals. Under certain assumptions[38], the best (minimum variance) unbiased linear estimator (BLUE) of β is obtained by minimizing the error sum of square[39],

$$Q = u'u = (y - X\beta)'(y - X\beta) \qquad (3.14)$$

In other words, the ordinary least squares method finds the estimates of the parameters ($\hat{\beta}$) by minimizing Q.

$$\sigma^2_{exrate} = \beta_0 + \beta_1\sigma^2_{goldp} + \beta_2\sigma^2_{platp} + \beta_3\sigma^2_{palladp} + \beta_4\sigma^2_{oilp} + \beta_5\sigma^2_{silvp} \qquad (3.15)$$

where β_i's are the estimated coefficients that minimize Q, and σ^2 is the measure of volatility (variance) of the indicated series.

3.3.2.4 Vector Autoregressive (VAR) Model

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[38] (i) The errors are independently and identically distributed with zero mean and constant variance; (ii) the xs are nonstochastic, hence independent of the residuals; (iii) the xs are linearly independent implying that **X'X** is non-singular.

[39] This is known as the Gauss-Markov theorem. For more details refer to Plackett (1950).

The main objective of this paper is to determine if there is volatility transmission from commodity prices to the nominal exchange rate in South Africa. One of the econometric techniques we use is the Granger causality, which was developed by Granger (1969). A stationary series, X_t, is said to Granger-cause another series, Y_t, if past and present values of X_t improve the forecast of Y_t. In this case, it is said that a one way causality from X_t to Y_t exists.

In this study, the Granger-causality tests are performed in a bivariate vector autoregressive (VAR) model.

Given the following bivariate VAR model;

$$\begin{bmatrix} Xt \\ Yt \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \Gamma_{11}(B) & \Gamma_{12}(B) \\ \Gamma_{21}(B) & \Gamma_{22}(B) \end{bmatrix} \begin{bmatrix} X_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{xt} \\ \varepsilon_{yt} \end{bmatrix} \tag{3.16}$$

$$= \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \Psi_{11}(B) & \Psi_{12}(B) \\ \Psi_{21}(B) & \Psi_{22}(B) \end{bmatrix} \begin{bmatrix} \varepsilon_{xt-1} \\ \varepsilon_{yt-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{xt} \\ \varepsilon_{yt} \end{bmatrix} \tag{3.17}$$

X_t is said to Granger-cause Y_t if $\Psi_{21}(B) \neq 0$ or $\Gamma_{21}(B) \neq 0$. Similarly, Y_t is said to Granger-cause X_t if $\Psi_{12}(B) \neq 0$ or $\Gamma_{12}(B) \neq 0$. In other words, X_t Granger-causes Y_t if $\Gamma_{21,i} \neq 0$ for $i = 1,2,...,p$ and Y_t Granger-causes X_t if $\Gamma_{12,i} \neq 0$ for $i = 1,2,...,p$.

Sometimes X_t can Granger-cause Y_t and Y_t Granger-cause X_t simultaneously. In this case we say there is a two-way causation between the two series. One the requirements in implementing the Granger causality is determining the optimal lag length, p. In this research, the lag length is determined by minimizing the Akaike Information Criteria (AIC).

The VAR model above is also used to compute the impulse response functions and variance decomposition between volatility in commodity prices and exchange rates. A detailed description of the impulse response functions and variance decomposition are provided in chapters two and three.

3.3.2 Data, Description and Source

This study uses daily as well as monthly commodity and exchange rate series that are used to compute the monthly return series. The data at a daily and monthly frequency, on exchange rate are obtained from the International Financial Statistics (IMF) database and are average rates. The daily commodity prices are spot closing prices and were collected from the online Deutsche Bundesbank Data Repository via Quandl. The monthly commodity data series were obtained from the World Bank database. The commodity prices are measured in dollars per troy ounce, whereas the exchange rate is measured in South African Rand per unit of US dollars. The data cover the period from January 1991 to June 2014, with 5,890 daily observations and 282 monthly observations. The series were transformed into continuously compounded returns, r_t, using the formula,

$$r_t = 100 * ln\left(\frac{p_t}{p_{t-1}}\right)$$

where p_t and p_{t-1} are the nominal exchange rate and commodity prices for periods, t and t -1, respectively.

Before any formal econometric analysis it is useful to visualize the dynamic behavior of the series by means of graphic inspection. Figures 3.1 and 3.2 present the graphical representation of the monthly prices and return series, while figure 3.3 provides the plots of the return series for the daily series. From the left panel of figures 3.1 and 3.2, there seems to be a general upward trend in all the series over the years examined. Also, a lot of commodity price and exchange rate fluctuations can be seen during the period of study, especially since the late 1990s. From figures 3.3 and the right column of figures 3.1 and 3.2, we can see that the return series exhibit periods of higher volatility followed by periods of tranquility. This phenomenon, known as volatility clustering, implies that the return variance is not constant, but rather varies through time. Volatility clustering also implies a strong autocorrelation in squared returns. A technical term given to this phenomenon is the ARCH effect.

3.4 Analysis of Results

3.4.1 Descriptive Statistics

The results of the summary statistics for the monthly and daily return series are presented in tables 3.1 and 3.2, respectively. The averages of the return series are all positive, suggesting that the prices of all commodities and the exchange rate have increased over time. This increase is corroborated by the graphs in figures 3.1 and 3.2 that show an upward trend in all the price series. With a mean of 1.06, palladium has the highest return. The standard deviation figures indicate that the returns on oil (retoilp) and palladium (retpalladp) are more volatile, whereas the returns on the exchange rate (retexrate) are the least volatile.

The measure of skewness indicates that exchange rate, gold, platinum, and silver price returns are positively skewed, indicating that they are right-tailed. The oil and palladium price returns are negatively, skewed indicating that they are left-tailed. The kurtosis measure indicates that all the return series have a kurtosis value greater than 3, indicating that all series are leptokurtic. These results suggest that the return series are not normally distributed, which is also supported by the rejection of the normality hypothesis test given by the Jarque-Bera test.

3.4.2 Analysis of the GARCH Model

The first step in a time series analysis is to determine the stationarity of the series, since most time series techniques require that the series be stationary. A time series is said to be stationary if its mean and variance are constant over time. In this study we use the Augmented Dickey-Fuller (ADF) test to determine the stationarity of the series.

A given time series y_t and its respective AR (p) process is expressed in equation 3.18

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \varphi_1 \Delta y_{t-1} + \dots + \varphi_{p-1} \Delta y_{t-p+1} + \epsilon_t \qquad (3.18)$$

where $\epsilon_t \sim iid(0, \sigma_\epsilon^2)$

The ADF test consists in testing the null hypothesis that $\gamma = 0$ that the series has unit root, against the alternative[40] that the series is stationary.

The results of the ADF and PP tests for the monthly are given in tables 3.3 and 3.4, respectively, whereas for the daily return series are given in tables 3.5 and 3.6 for the ADF and PP, respectively. As the tables show we selected an ADF equation with a constant, which implies that in terms of equation 3.18, $\alpha \neq 0$ and $\beta = 0$, depending on whether the underlying data generating process is assumed to have drift and time trend. The optimal lag length (p) is chosen by minimizing the Akaike Information Criteria, given in equation 3.19.

$$\text{AIC} = -2\ln L + 2k \qquad (3.19)$$

[40] The alternative hypothesis is a one sided test that $\gamma < 0$. The critical values are obtained from Davison and Mackinnon (1993), and the test procedure involves determining if $\alpha = 0$, $\beta = 0$. For more details on the ADF refer to Enders (2010).

where L is the maximum log likelihood of the model and k is the number of parameters estimated.

For the monthly return series the results of the ADF indicate that, for the return on the exchange rate (retexrate), the test statistic is - 4.92; this is greater in absolute value than the critical value of -3.43 at the 1% significance level. For the other series in the table, the results also indicate that the test statistics are larger than the critical values at the 1% significance level. These results imply imply that we reject the null hypothesis that the series have unit root and conclude that they are all stationary. Except for return on palladium prices (retpalladp) which has an absolute value of $\gamma = 0.74$, the absolute value of the coefficient γ for all the other series are greater than 0.9, implying that they are indeed different from zero. The PP test results also indicate that the monthly return series are stationary.

The unit root test results for the daily returns are presented in table 3.4. The test statistic for the null hypothesis that the return on the gold price (retgoldp) is -24.37 which is way greater than the critical value, hence we reject the null and conclude that retgoldp is stationary. Similarly, the test statistic for the test that the return on silver (retsilvp) is -57.54, which is larger than the 1% significance level critical value of -3,43, hence we reject the null hypothesis that retsilvp has unit root and conclude that it is stationary. The tests for other series in table 3.4 yield the same findings. Hence, we conclude that similar to the monthly return series, the daily return series are stationary. The results in table 3.4 also indicate that with the exception of the test of stationarity of retpalladp wich has $\gamma = 0.74$ in absolute value, the values of γ for the other series are greater than 1.0 in absolute value, which is significantly larger than zero. The results of the PP test also support the conclusion that all the volatility series are stationary, since in all cases we reject the null hypothesis that the series have unit root.

Having determined the stationarity of the series, next we proceed to estimate the volatility of the series. First, we start by estimating the conditional volatility and then the realized volatility.

As it was discussed earlier, the first step in estimating a GARCH model, is to determine if the use of GARCH process is justified. The results of the ARCH –LM test which are presented in table 3.1 indicate that for all series, the p-value for the test is less than 0.5 indicating that in all cases we reject the null hypothesis that the are no ARCH-effects in the return series, hence the use of GARCH technique is justified.

The results of the GARCH (1,1)[41] process for the monthly return series are presented in table 3.5. They indicate that the coefficients of the variance equation are statistically significant. The diagnostic tests for the GARCH(1,1) models in table 3.5 reveal that no ARCH effect remain, implying that GARCH(1,1) model is suitable for modelling the series. Moreover, the sum of the lagged value of the conditional variance in the variance equation are all positive and statistically significant. Their sum is less than unity, implying that the estimated models are mean reverting, but are close to unity, implying large persistence in volatility for all models. The volatility estimates obtained from the GARCH (1,1) models are displayed in figure 3.4. Analysis of the plots indicates that for all series under study, volatility has been present throughout the study period, with volatility being less evident in the 1990s followed by more volatility since 2000. Moreover, the volatility behavior captured in figure 3.4 is similar to the volatility variation in the return series for each individual series, displayed in figures 3.1 and 3.2.

3.4.4 Analysis of Realized Volatility

Figure 3.5 shows the plots of the realized volatilities for the series under study. A look at the exchange rate volatility plot reveals some spikes in volatility in mid 1990s which also coincides with spikes in the volatilities of the commodity prices under study. Frankel (2007) explains this due to South African transition to democracy which led to the country's opening to the international markets, hence the effect of the commodity prices on the South African Exchange rate. Moderate spikes in the realized volatilities in exchange rate are also observed in the late 1990s, 2002 and 2006. These spikes in volatilities can be attributed to the fall in mineral exports in the late1990s, and natural resource booms observed in 2002-2006, which led to the respective fall and rise in South African Rand, Frankel (2007). The largest spike in exchange rate realized volatility, which also coincides with spikes in the realized volatility in the commodity prices was observed around 2008, during the recent world economic downturn.

[41] The choice of GARCH (1,1) over other GARCH specifications was based on the fact that the literature suggests that GARCH (1,1) is superior to other GARCH specifications. For more details see Hansen and Lunde (2001), Engle (2001) and Engle and Patton (2001).

For a very easy comparison between the two volatility estimation methods, figure 3.6 puts figures 3.4 and 3.5 together, where the solid line represents the volatilities from the GARCH models, whereas the thin and dotted line is the volatility from the realized volatility estimation method. Clearly, from figure 3.6 the volatility series from the two volatility estimation series appear to be similar.

Having estimated the volatility series (using both parametric and non-parametric approaches) now we can answer the main question of the paper, which is if there are volatility transmission from commodity prices to nominal exchange rate in South Africa, which is answered in the following sections.

However, before we carry out the volatility transmission analysis, as it is customary we will analyze the stationarity of the volatility series. Tables 3.6 and 3. 7 provide the unit root test results for the conditional (parametric) and realized (non-parametric) volatility series, respectively. The results in both tables indicate that the test statistics are greater than their respective critical values, hence we reject all the null hypothesis and conclude that all the volatility series under both approaches (conditional and realized volatility) are stationary. Tables 3.8 and 3.9 present the descriptive statistics for the conditional volatility and realized volatility series, respectively.

3.4.5 Granger-Causality Results Analysis

The objective in this chapter is to assess the volatility transmission between commodity prices and the nominal exchange rate in South Africa. In this section we analyze whether volatilities in commodity prices can improve our prediction of volatilities in the exchange rate. The results of such analyzes which are given by Granger-causality test are reported in tables 3.11 and 3.12 for the conditional (GARCH) and realized volatility estimation methods, respectively. Five bivariate Vector Autoregressive (VAR) model were employed in order to carry out the Granger-causality between the commodity prices and the exchange rate. The specifications of all the bivariate VAR models of the volatilities are presented in table 3.10. As the table indicates all the VAR models are estimated using a constant deterministic, and the number of optimal lags were chosen using the Akaike Information Criteria.

The results of the of the Granger-causality indicate that the p-value of the null hypothesis that there is no granger-causality from any commodity price volatility to the volatility in the exchange rate is less than 0.05, which suggests that for every test we reject the null hypothesis.

For instance, the p-value for the test volatility in gold prices does not Granger-cause volatility in exchange rate is 0.002 for the parametric volatility (GARCH) approach. This implies that we can reject the null hypothesis and conclude that volatility in gold prices do Granger-cause volatility in South African exchange rate. The p-values for the test that other commodity price volatilities do not Granger-cause volatility in exchange rate using the parametric volatility approach (GARCH) are even smaller than 0.02. This implies that we can state that there is evidence to infer that using the parametric volatility approach (GARCH) model, volatility in commodity prices studies do Granger-cause volatility in the exchange rate.

The results of the Granger-causality test that volatilities in commodity prices do not improve predictions in the volatility in exchange rate for the non-parametric (realized) volatility model approach are given in table 3.12. The p-value of the Granger-causality test that volatility in palladium prices do not Granger-cause volatility in exchange rate is 0.003, which implies that we can reject the null hypothesis and conclude that volatility in palladium prices do Granger-cause volatilities in exchange rate. The p-values of the rest of the Granger-causality tests (from volatility in commodity prices to volatility in exchange rate) in table 3.12 are even smaller than 0.003, which implies that similar to the parametric volatility approach, results from realized volatility model suggest enough evidence to conclude that volatility in prices of the commodity in this study can help improve the prediction of the volatility of the South African exchange rate.

3.4.6 Impulse Response Functions and Variance Decomposition

In this section the analysis of volatility transmission from commodity prices to nominal exchange rate is carried out by means of Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) analysis. IRF and FEVD are standard tools for investigating the relationship between variables in a VAR model. The impulse response functions gives the time path of the dependent variable in the in the VAR, to shocks from the explanatory variables, whereas the FEVD determines how much of the forecast error variance for any variable in a system, is explained by its own innovations as well as innovations from other variables in the system, over a series of time horizons. The results of the impulse response functions of volatility in exchange rate to shocks in volatility in commodity prices under conditional volatility approach are presented on the left hand side of the figure 3.7, and those under realized volatility model are shown on the right hand side.

The left hand side of figure 3.7 shows that the impact of a one standard deviation shock in the volatility of commodity prices results a positive response in the volatility in exchange rate. The response to shock in volatility in gold prices is the largest and reaches its peak after 2 months, and the effect dies out after about 14 months. The next largest effect on the volatility in exchange rate is due to shocks in volatility in platinum and oil prices. The effect of the shock on platinum price volatility reaches its peak after 2 months, while the effect of the exchange rate reaches its peak after just one month. Both effects die out within a year after they reach the peak. Shock to volatility in silver price, which has the lowest impact on the volatility in exchange rate reaches its peak after one month, and similar to the result of the previous socks, this shock also dies away within a year.

The results of the response of shocks in volatility of exchange rate due to shocks in commodity under realized volatility approach are very similar to the ones under conditional volatility approach mentioned above, in the sense that a positive shock to volatilities in commodity prices leads to a larger fluctuations in the exchange rate. However, similar shocks in commodity prices tend to have a slightly larger effect under the realized volatility approach. For instance, a shock to volatility in gold prices has the largest effect on volatility in exchange rate of just above 0.20 under the realized volatility, but a similar shock had an effect of about 0.16, and like in the case of conditional volatility, the effect of the shock under realized volatility approach reaches its peak in 2 months, and dies out within a year.

The results of the FEDV analysis are given in tables 3.16 through 3.20 for the realized volatilities and from tables 3.21 through tables 3.25 for the conditional volatilities. The results under both volatility models are consistent with the impulse response function results. Under both models, the volatility in gold prices tend to explain a higher variation in volatility in exchange rate than variations in price volatility of other commodities.

In the following section the analysis of the volatility spillover from the commodity prices to exchange rate is extended by estimating an ordinary least square model with volatility in exchange rate as the dependent variable and volatility in the commodity prices as the explanatory variables.

3.4.7 Analysis of the OLS Results

Having found out that there is strong evidence that volatility in all commodity prices do Granger-cause volatility in exchange rate, next we carry out the second test of transmission of volatility from the commodity prices to exchange rate by employing Ordinary Least Squares (OLS) method. For a better analysis of the effect of volatility in commodity price of the exchange rate volatility, two OLS results are ported. The first OLS results, which are reported in tables 3.13 and 3.14 the explanatory variables are the contemporaneous volatility series, where table 3.13 use the volatility series from the conditional estimation technique, whereas table 3.14 uses the volatility series from the realized volatility estimation method.

The results in table 3.12 show that the effect of the contemporaneous volatility in gold prices on exchange rate volatility is 0.17 and statistically significant. This implies that increasing the volatility (variance) by one unit, the volatility in the exchange rate increases by 0.17 in the current month. The impact of the volatility in platinum prices on the volatility in exchange rate is 0.03, but it is not statistically significant. The impact of the volatility in palladium and silver prices on exchange rate volatility is 0.11 and 0.13, respectively, and but only the effect of palladium is statistically significant. Again, the first figure, implies that a change in the volatility (variances) in palladium by one unit leads to an increase in the exchange rate volatility by 0.11 contemporaneously, whereas the second number implies that increasing the variance of the silver price by one unit leads to an increase in volatility in exchange rate by 0.13. Finally, the effect of the change in oil price volatility by one unit on exchange rate volatility is 0.10, and it is statistically significant.

Table 3.14 shows that with the exception of volatilities in platinum and silver prices, volatility from all other commodities have a statistically impact on the volatility in exchange rate. For instance, increasing the volatility in gold prices by one unit increases the variance in the exchange rate by 0.168 in the current month, whereas an increase in oil price volatility by the same amount leads to an increase in exchange rate volatility by 0.058.

To further analyze how volatility in commodity prices affect exchange rate volatility we also report OLS results where the explanatory variables are contemporaneous volatilities as well as lags of the volatilities in the commodity prices. In order to determine the optimal number of lags, we employed the Akaike Information Criteria. The optimal lag length chosen is seven, and the OLS results for both conditional and realized volatility series are shown in table 3.15. The values of the coefficients given in table 3.15 represent the overall effect of the volatility in commodity prices on the exchange rate volatility, which is computed by adding the effects in all lags. As the results show a change in volatility in gold prices has an overall effect 0.21 and 0.191

change in exchange rate volatility, for conditional and realized volatility methods, respectively. Similarly, Overall effect of volatility in silver prices on exchange rate volatility for the conditional volatility method is 0.067, and for the realized volatility approach is 0.071. In order to analyze the statistical significance of these overall effects we carry out a series of exclusion F-tests, where the unrestricted model is the OLS with the seven lags in all commodity price volatilities and the five restricted models are obtained by eliminating the effect of each commodity price volatility one at a time. The F-test carried out is given in equation 3.20.

$$F = \frac{(RSS_r - RSS_u)/_{m}}{RSS_u/_{(n-k-1)}} \tag{3.20}$$

Where RSS_r and RSS_u are the residuals sum squares for the restricted models and unrestricted model, respectively, m is the degrees of freedom for the numerator, which is equal tp eight, and $n - k - 1$ is the degree of freedom for the denominator, which is equal to 239. A rejection of the null hypothesis in this case means that eliminating the lags of the volatility of the commodity in question from the unrestricted model would reduce the how much the volatility in the exchange rate is explained by the model very significantly.

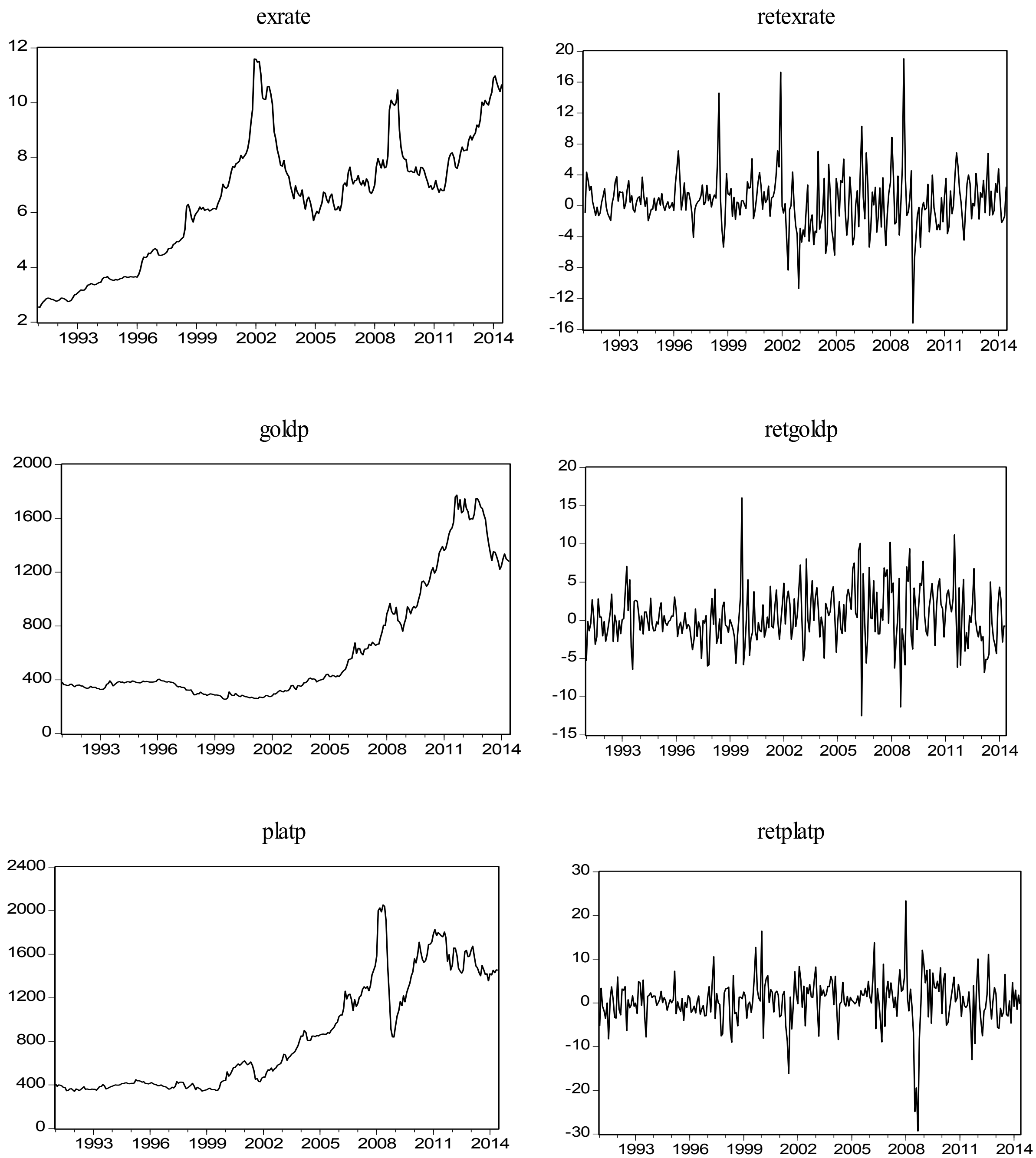
The results of this tests are also reported in table 3.15, under the "exclusion test heading". As the results show the only the effects of volatilities in gold, palladium, and oil prices appear to be statistically significant. These results appear to be consistent with the previous results in this chapter especially, for volatility in gold and oil prices that show that increase in gold and oil price volatilities tend to have a statistically significant effect on the volatility in exchange rate.

3.5 Conclusion

In this study we investigate the volatility transmission from commodity prices to nominal exchange rate in South Africa. Volatilities were estimated using both parametric (GARCH) as well as non-parametric volatility (realized volatility) approaches. To estimate the parametric volatilities, monthly series covering the period Jan-91 to June-2014 were used. For the non-parametric volatility approach, daily series from 01/013/91 to 06/30/2014 were used to estimate monthly realized volatility series. The series used are nominal exchange rate, gold prices, platinum prices, palladium prices, oil prices, and silver prices. Granger-causality results indicate that volatility of every single commodity price granger-causes volatility in the nominal exchange rate. Next, the study is extended by applying OLS method of volatility in the exchange rate on commodity the volatility of the exchange rate. The OLS results suggest that from both volatility approaches, volatility in gold, oil and to some extend palladium prices have a statistically significant effect on the nominal exchange rate volatility.

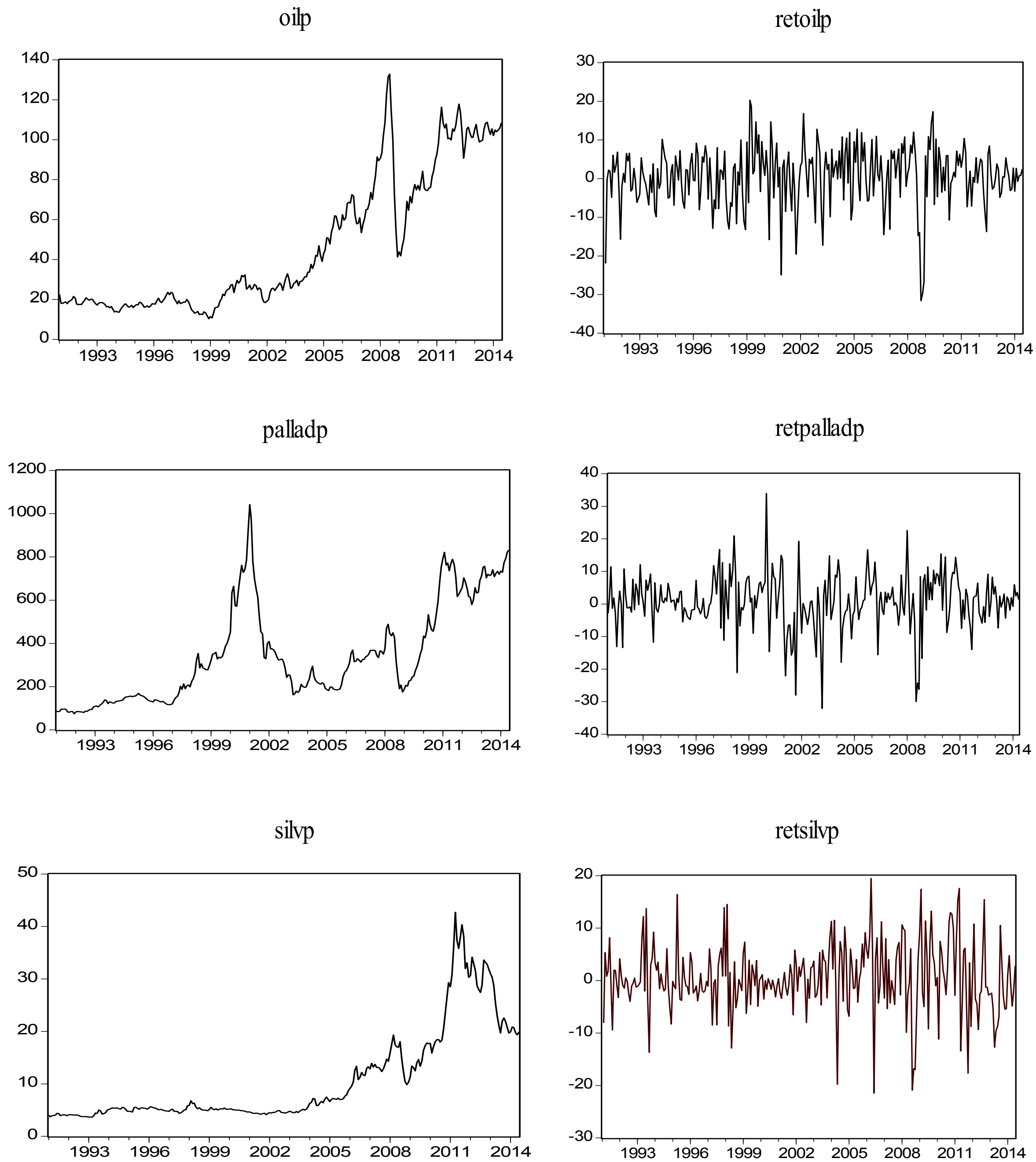
Overall results indicate that there is evidence of fluctuation spillover from commodity prices and nominal exchange rate in South Africa. These results imply that policy makers need to take into account the impact of commodity prices in formulating economic policies, exchange rate in particular. Similarly, investors and exporters need to pay close attention to the volatilities in commodity prices, since it has impact on the exchange rate volatilities, which in turn affects the value of their investments.

Figure 3.1 Plots of monthly prices and returns series[42]



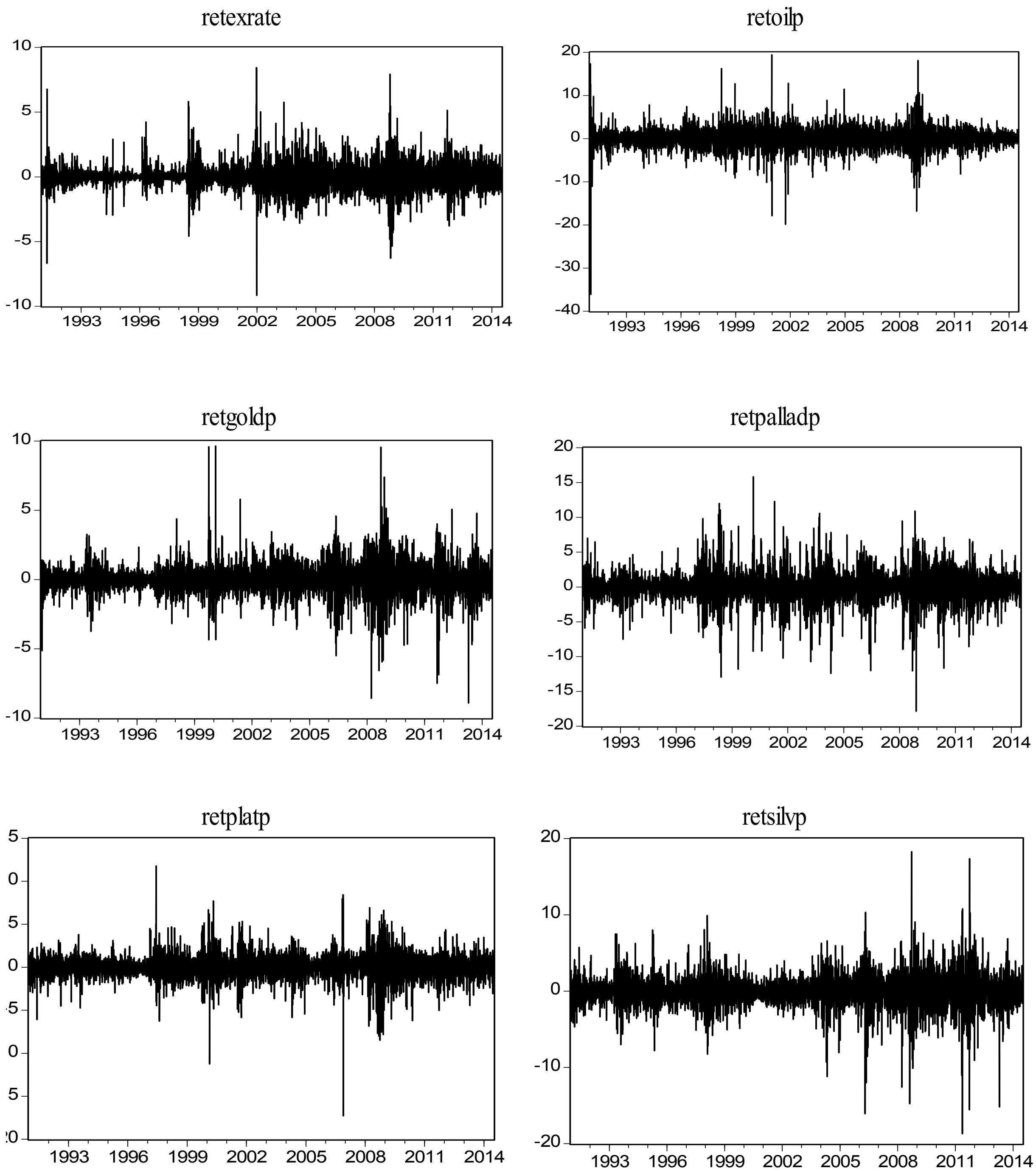
[42] Notes: exrate is the exchange rare, goldp is the gold price, platp is the platinum prices, and retexrate, retgoldp, and retplatp are their respective returns.

Figure 3.2 Continuation of figure 3.1[43]



43 Notes: oilp is the oil price, palladp is the palladium price, silvp is the silver price and retoilp, retpalladp, and retsilvp are their respective returns.

Figure 3.3 Line plots for the daily return series[44]



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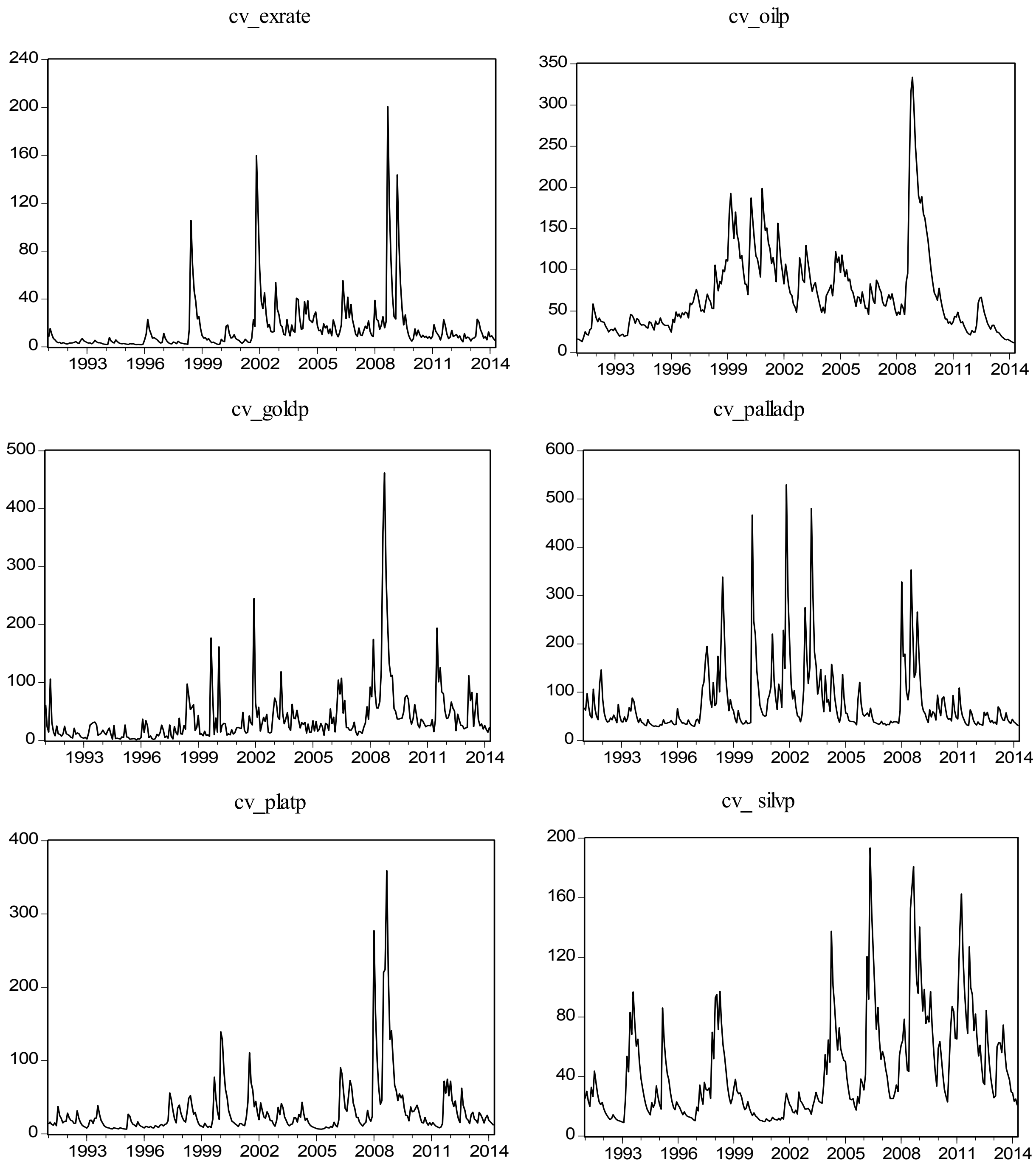
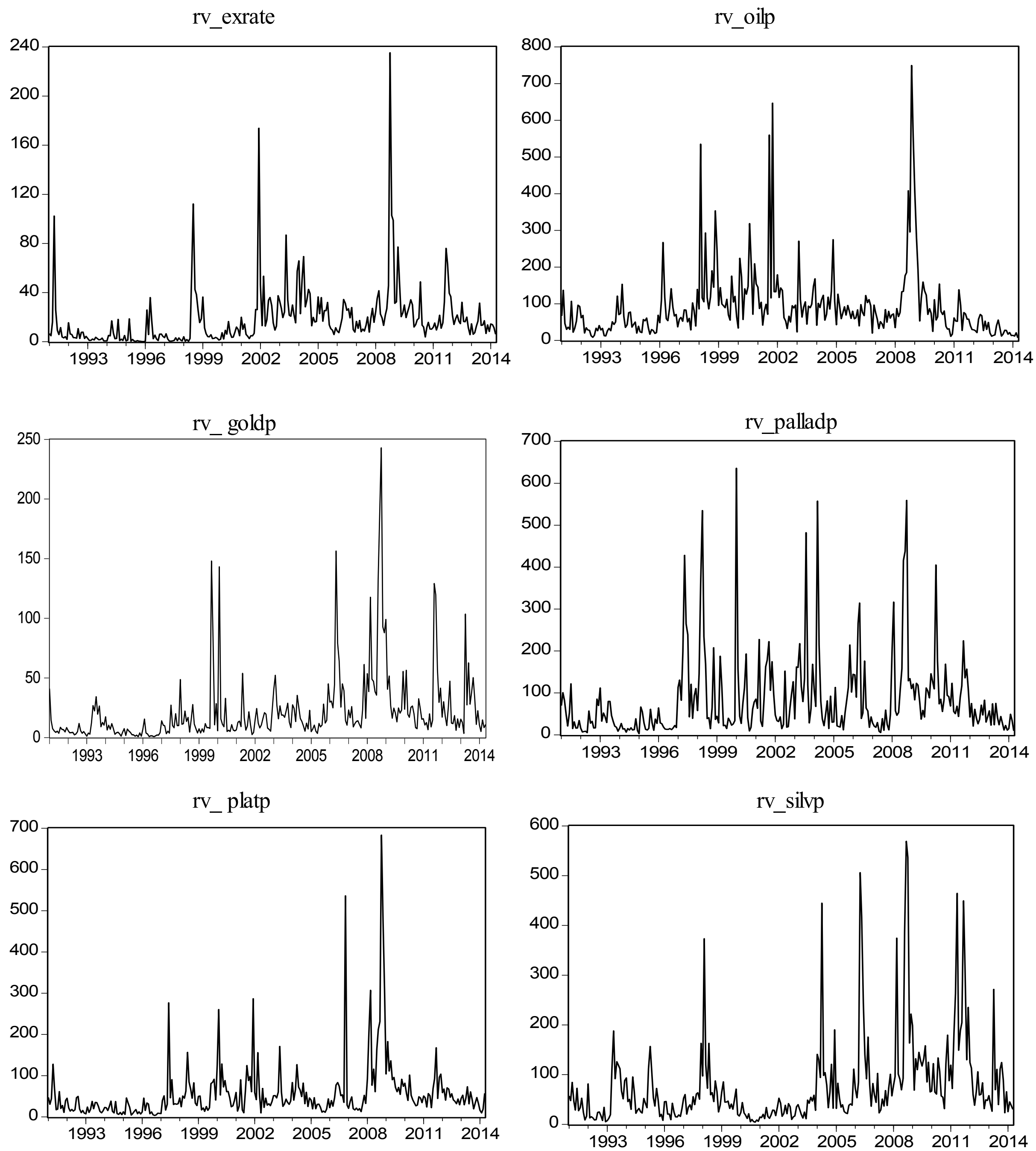
[44] Notes: retxrate, retgoldp, retplatp, retoilp, retpalladp, and retsilvp are return of the exchange rate, gold prices, platinum prices, oil prices, palladium prices, and silver prices, respectively.

Figure 3.4 Conditional (GARCH) Volatility Estimates



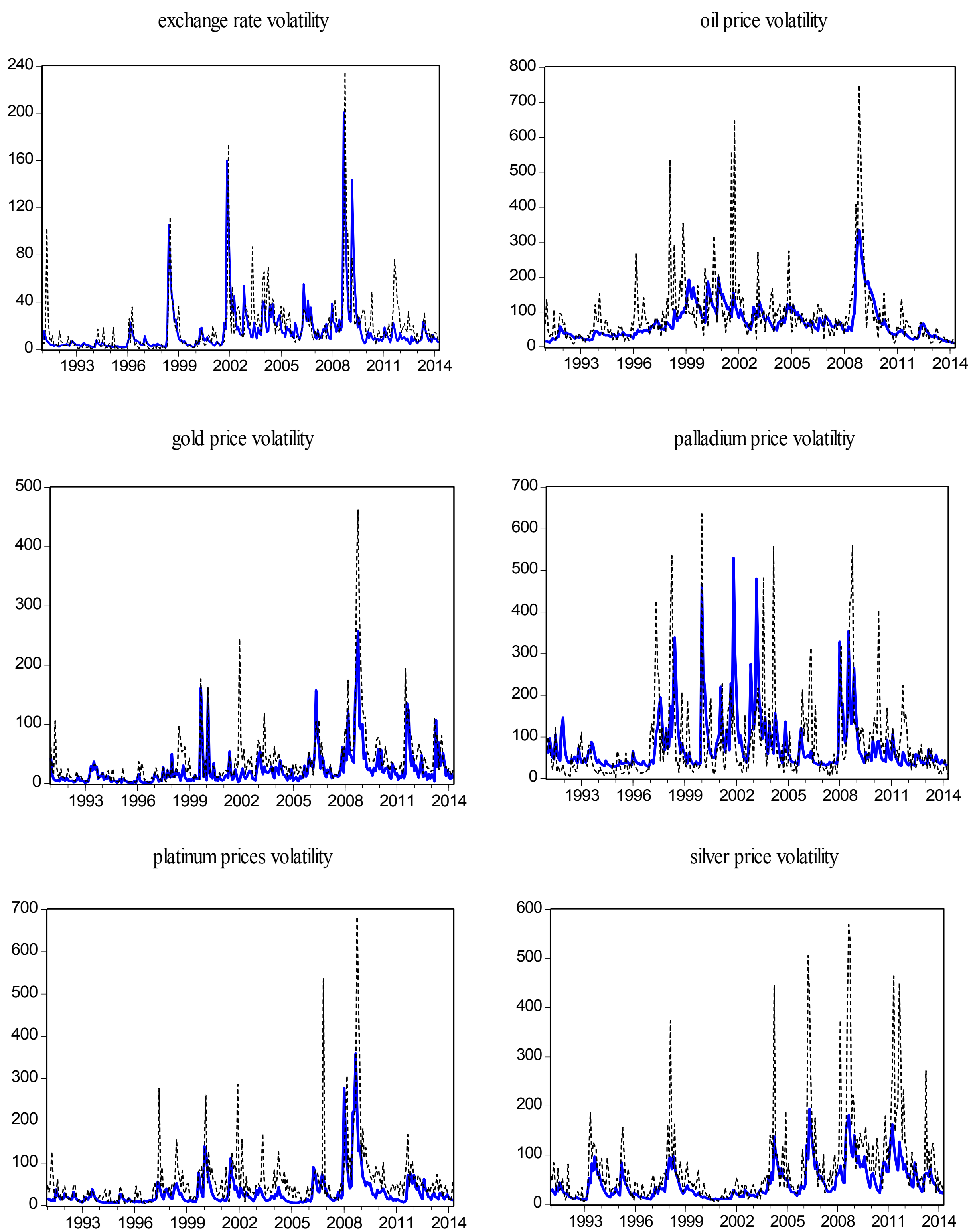
Notes: cv_exrate, cv_goldp, cv_platp, cv_oilp, cv_palladp and cv_silvp are the conditional volatilities for the return on the exchange rate, gold, platinum, oil, palladium, and silver.

Figure 3.5 Realized Volatility



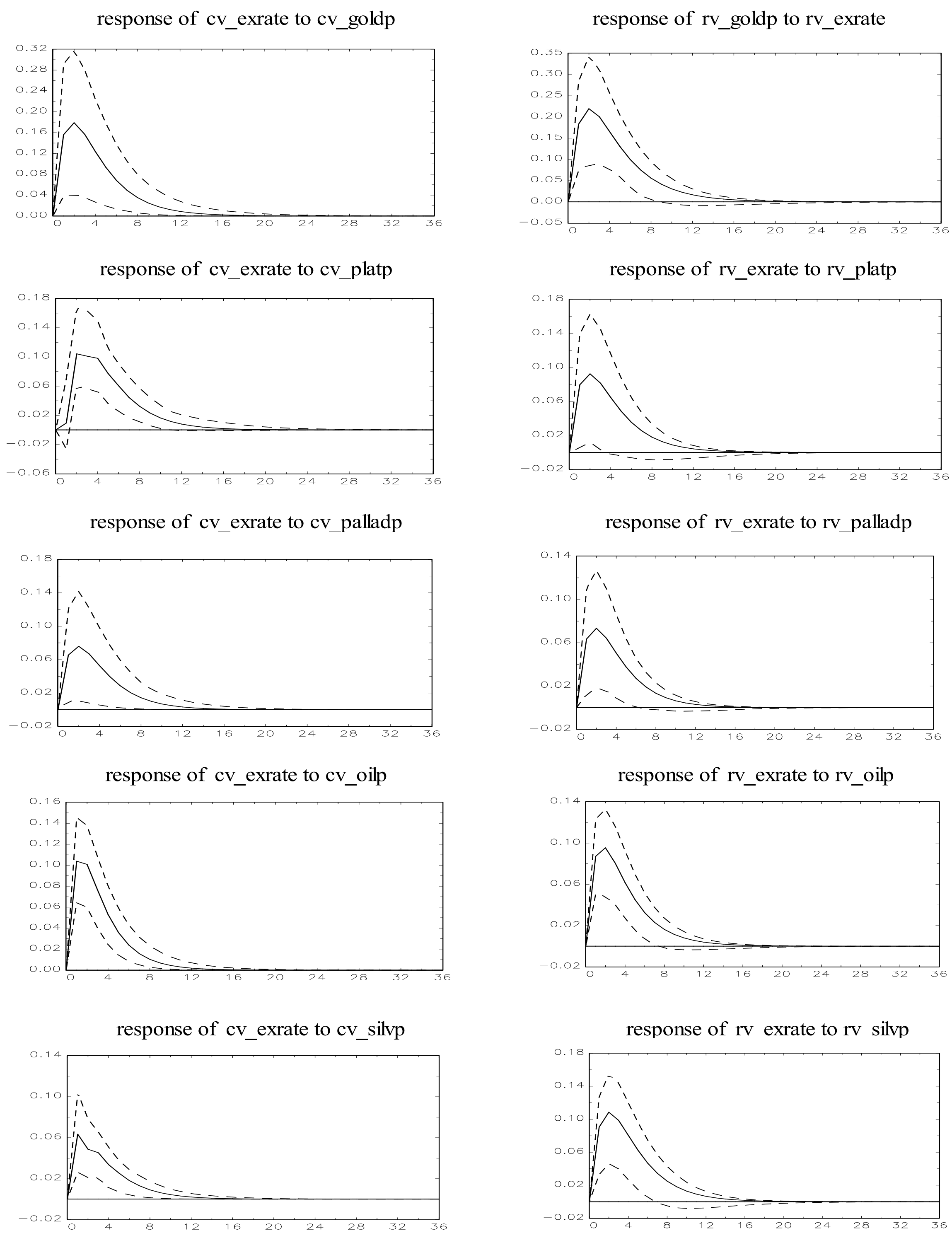
Notes: rv_exrate, rv_goldp, rv_platp, rv_oilp, rv_paladp, rv_silvp are the realized volatility series for the exchange rate, gold, platinum, oil, palladium and silver, respectively.

Figure 3.6 Conditional and Realized Volatilities



Notes: The solid line is the conditional volatility and the dotted line is the realized volatility

Figure 3.7 Impulse Response Functions for the Volatility in Exchange Rate



Notes: The cholesky ordering is (volatility in commodity price, volatility in exchange rate). The vertical axis represents the value of the response variable and the horizontal axis represents the number of periods.

Table 3.1 Summary Statistics for the monthly return series

	retexrate	retgoldp	retplatp	retoilp	retpalladp	retsilvp
Mean	0.51	0.94	0.96	1.06	1.31	1.07
Median	0.43	0.83	1.11	2.37	1.54	0.76
Maximum	19.0	17.2	32.2	25.4	37.1	23.1
Minimum	-15.2	-18.9	-24.4	-27.8	-36.1	-20.4
Std. Dev.	3.5	4.4	5.7	8.3	8.8	6.6
Skewness	0.7	0.5	0.6	-0.5	-0.1	0.2
Kurtosis	9.0	6.1	8.4	4.0	6.3	4.1
Jarque-Bera	442	121	361	23	127	16
Probability	0.00	0.00	0.00	0.00	0.00	0.00
ARCH LM	16.32	19.49	53.36	61.55	20.85	38.01
p-value	0.012	0.003	0.000	0.000	0.002	0.000
Observations	281	281	281	281	281	281

Notes: retexrate, retgoldp, retplatp, retoilp, retpalladp, and retsilvp are the returns on exchange rate, gold prices, platinum prices, oil prices, palladium prices, and silver prices, respectively.

Table 3.2 Summary Statistics for the daily return series

	retexrate	retgoldp	retplatp	retoilp	retpalladp	retsilvp
Mean	0.02	0.02	0.02	0.02	0.04	0.03
Median	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	8.43	9.64	11.78	19.44	15.84	18.28
Minimum	-9.16	-8.91	-17.28	-36.12	-17.86	-18.69
Std. Dev.	0.93	1.03	1.34	2.24	2.02	1.93
Skewness	0.33	0.21	-0.55	-0.70	-0.20	-0.44
Kurtosis	11.45	12.84	13.76	21.14	9.54	13.16
Jarque-Bera	1020	354	418	371	486	535
Probability	0.00	0.00	0.00	0.00	0.00	0.00
Observations	5891	5891	5891	5891	5891	5891

Notes: retexrate, retgoldp, retplatp, retoilp, retpalladp, and retsilvp are the returns on exchange rate, gold prices, platinum prices, oil prices, palladium prices, and silver prices, respectively.

Table 3.3 Table 3 Augmented Dickey-Fuller (ADF) Test for the monthly return series

Series	Model	Lags	γ	Test Statistic
retexrate	c	7	-0.66	-4.92*
retgoldp	c	2	-0.95	-14.92*
retplatp	c	4	-0.94	-7.05*
retoilp	c	6	-0.94	-6.94*
retpalladp	c	1	-0.74	-10.29*
retsilvp	c	1	-0.91	-11.90*

Notes: The null hypothesis for the ADF test is that the series has unit root. The critical values are -3.43, -2.86 and -2.57 for 1%, 5% and 10% significant levels, respectively. The optimal number of lags was chosen based on AIC.

Table 3.4 Unit Root Test – Philip Peron (PP) Test for the monthly return series

Series	Model	Test Stat.
retexrate	c	-12.12*
retgoldp	c	-14.90*
retplatp	c	-12.84*
retoilp	c	-13.44*
retpalladp	c	-12.67*
retsilvp	c	-13.80*

Notes: "*" indicates rejection of the null hypothesis. The critical values for PP test for 1%, 5% and 10% significance levels for model with "c" are -3.43, -2.86, and -2.57; for model with "c,t" are -3.96,-3.41, and -3.13; and for a model with no deterministic trend are -2.56, -1.93, -1.61.

Table 3.5 Unit Root Test - Augmented Dickey-Fuller (ADF) Test for the daily return series

Series	Model	Lags	γ	Test Statistic
retexrate	c	5	-1.05	-33.32*
retgoldp	c	10	-1.09	-24.37*
retplatp	c	2	-1.01	-34.08*
retoilp	c	1	-1.04	-29.71*
retpalladp	c	4	-0.94	-33.47*
retsilvp	c	1	-1.11	-57.54*

Notes: "*" indicates rejection of the null hypothesis. The critical values for PP test for 1%, 5% and 10% significance levels for model with "c" are -3.43, -2.86, and -2.57; for model with "c,t" are -3.96,-3.41, and -3.13; and for a model with no deterministic trend are -2.56, -1.93, -1.61.

Table 3.6 Unit Root Test - Philips Peron Test for the daily return series

Series	Model	Test Stat.
retexrate	c	-77.21*
retgoldp	c	-82.27*
retplatp	c	-73.65*
retoilp	c	-77.21*
retpalladp	c	-73.65*
retsilvp	c	-86.16*

Notes: "*" indicates rejection of the null hypothesis. The critical values for PP test for 1%, 5% and 10% significance levels for model with "c" are -3.43, -2.86, and -2.57; for model with "c,t" are -3.96,-3.41, and -3.13; and for a model with no deterministic trend are -2.56, -1.93, -1.61.

Table 3.7 GARCH (1, 1) models for the return series

	retexrate	retgoldp	retplatp	retoilp	retpalladp	retsilvp
β_0	0.615	0.843	0.903	1.080	1.077	0.731
	[0.001]	[0.009]	[0.030]	[0.026]	[0.110]	[0.121]
β_1	0.311	0.151	0.136	0.198	0.314	0.154
	[0.000]	[0.032]	[0.077]	[0.005]	[0.000]	[0.024]
ω	0.064	2.449	7.076	2.599	14.900	6.578
	[0.219]	[0.016]	[0.000]	[0.094]	[0.000]	[0.012]
α_1	0.036	0.116	0.152	0.158	0.376	0.150
	[0.120]	[0.028]	[0.002]	[0.003]	[0.001]	[0.019]
γ_1	0.962	0.759	0.638	0.798	0.467	0.702
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$\alpha_1 + \gamma_1$	0.997	0.875	0.790	0.956	0.843	0.852
ARCH LM	2.752	2.227	4.757	4.306	0.918	2.327
	[0.839]	[0.898]	[0.575]	[0.635]	[0.989]	[0.887]

Notes: The numbers in. brackets are p-values.

Table 3.8 Unit Root Test - Augmented Dickey-Fuller Test for the conditional volatility series

Series	Model	Lags	γ	Test Statistic
cv_exrate	c	6	-0.22	-3.98*
cv_goldp	c	1	-0.18	-5.13*
cv_platp	c	8	-0.33	-3.77*
cv_oilp	c	1	-0.12	-5.23*
cv_palladp	c	2	-0.17	-3.43*
cv_silvp	c	7	-0.16	-4.19*

Notes: "*" indicates rejection of the null hypothesis, that the series has unit root. The critical values for PP test for 1%, 5% and 10% significance levels for model with "c" are -3.43, -2.86, and -2.57; for model with "c,t" are -3.96, -3.41, and -3.13; and for a model with no deterministic trend are -2.56, -1.93, -1.61.

Table 3.9 Unit Root Test – Phillips-Perron Test

Series	Model	Test Stat.
cv_exrate	c	-10.69*
cv_goldp	c	-5.25*
cv_platp	c	-11.15*
cv_oilp	c	-6.43*
cv_palladp	c	-10.58*
cv_silvp	c	-4.54*

Notes: "*" indicates rejection of the null hypothesis, that the series has unit root. The critical values for PP test for 1%, 5% and 10% significance levels for model with "c" are -3.43, -2.86, and -2.57; for model with "c,t" are -3.96, -3.41, and -3.13; and for a model with no deterministic trend are -2.56, -1.93, -1.61.

Table 3.10 Augmented Dickey-Fuller Test for the realized volatility series

Series	Model	Lags	γ	Test Statistic
rv_exrate	c	1	-0.52	-8.10*
rv_goldp	c	5	-0.32	-4.76*
rv_platp	c	1	-0.52	-7.68*
rv_oilp	c	1	-0.33	-5.75*
rv_palladp	c	2	-0.50	-7.26*
rv_silvp	c	3	-0.30	-4.40*

Notes: "*" indicates rejection of the null hypothesis, that the series has unit root. The critical values for PP test for 1%, 5% and 10% significance levels for model with "c" are -3.43, -2.86, and -2.57; for model with "c,t" are -3.96, -3.41, and -3.13; and for a model with no deterministic trend are -2.56, -1.93, -1.61.

Table 3.11 Unit Root Test - Philips Peron Test for the realized volatility series

Series	Model	Test Stat.
rv_exrate	c	-10.71*
rv_goldp	c	-8.47*
rv_platp	c	-11.16*
rv_oilp	c	-17.23*
rv_palladp	c	-10.41*
rv_silvp	c	-10.97*

Notes: "*" indicates rejection of the null hypothesis. The critical values for PP test for 1%, 5% and 10% significance levels for model with "c" are -3.43, -2.86, and -2.57; for model with "c,t" are -3.96,-3.41, and -3.13; and for a model with no deterministic trend are -2.56, -1.93, -1.61.

Table 3.12 Descriptive statistics of the conditional variance series

	cv_exrate	cv_goldp	cv_platp	cv_oilp	cv_palladp	cv_silvp
Mean	19.02	20.21	38.86	70.59	95.19	44.42
Median	11.98	16.15	24.02	58.57	59.06	31.19
Maximum	296.33	87.20	522.89	333.67	818.75	176.47
Minimum	0.12	10.77	2.58	11.49	11.30	10.04
Std. Dev.	28.54	11.32	54.34	50.75	101.56	33.01
Skewness	5.84	2.46	4.76	1.96	3.08	1.42
Kurtosis	50.66	10.30	32.38	8.46	16.66	4.83
Jarque-Bera	28088	905	11126	527	2621	133
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	281	281	281	281	281	281

Notes: cv_exrate, cv_goldp, cv_platp, cv_oilp, cv_palladp and cv_silvp are the conditional volatilities for the return on the exchange rate, gold, platinum, oil, palladium, and silver.

Table 3.13 Descriptive statistics of the realized volatility series

	rv_exrate	rv_goldp	rv_platp	rv_oilp	rv_palladp	rv_silvp
Mean	18.00	21.94	36.96	91.90	84.17	74.05
Median	11.33	12.10	23.27	69.66	50.55	47.39
Maximum	289.81	242.89	564.93	789.16	635.63	566.50
Minimum	0.19	0.70	2.26	7.28	3.00	4.17
Std. Dev.	27.42	30.14	54.03	96.29	98.42	84.38
Skewness	5.87	3.66	5.48	3.70	2.84	3.01
Kurtosis	50.68	19.82	42.64	20.95	12.72	13.86
Jarque-Bera	28231	3939	19806	4413	1483	1806
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Observations	281	281	281	281	281	281

Notes: rv_exrate, rv_goldp, rv_platp, rv_oilp, rv_paladp, rv_silvp are the realized volatility series for the exchange rate, gold, platinum, oil, palladium and silver, respectively.

Table 3.14 Vector Autoregressive model for the Granger-causality test, IRF and FEVD

Model	Deterministic trend	Number of lags (conditional volatility)	Number of lags (Realized volatility)
Model A	c	6	4
Model B	c	7	3
Model C	c	5	4
Model D	c	3	5
Model E	c	4	4

Notes: Models A, B, C, D and E are bivariate VAR models of exchange rate volatilities with volatilities in prices of gold, platinum, oil, palladium, and silver, respectively. The number of lags was chosen based on AIC.

Table 3.15 Granger causality-conditional volatility in exchange rate and commodity prices

Null Hypothesis	F-statistic	probability
cv_goldp does not Granger cause cv_exrate	4.10	0.00**
cv_exrate does not Granger cause cv_goldp	1.08	0.30
cv_platp does not Granger cause cv_exrate	6.08	0.00**
cv_exrate does not Granger cause cv_platp	1.38	0.24
cv_oilp does not Granger cause cv_exrate	7.07	0.01*
cv_exrate does not Granger cause cv_oilp	0.16	0.69
cv_palladp does not Granger cause cv_exrate	3.74	0.01**
cv_exrate does not Granger cause cv_palladp	0.97	0.17
cv_silvp does not Granger cause cv_exrate	3.53	0.02*
cv_exrate does not Granger cause cv_silvp	1.73	0.54

Notes: "**" indicates rejection of the null hypothesis. cv_exrate, cv_goldp, cv_platp, cv_oilp, cv_palladp and cv_silvp are the conditional volatilities for the return on the exchange rate, gold, platinum, oil, palladium, and silver.

Table 3.16 Granger causality test realized volatility- exchange rate and commodity prices

Null Hypothesis	F-statistic	probability
rv_goldp does not Granger cause rv_exrate	4.10	0.00**
rv_exrate does not Granger cause rv_goldp	1.08	0.30
rv_platp does not Granger cause rv_exrate	6.08	0.00**
rv_exrate does not Granger cause rv_platp	1.38	0.24
rv_oilp does not Granger cause rv_exrate	7.07	0.01*
rv_exrate does not Granger cause rv_oilp	0.16	0.69
rv_palladp does not Granger cause rv_exrate	3.74	0.01*
rv_exrate does not Granger cause rv_palladp	0.97	0.17
rv_silvp does not Granger cause rv_exrate	3.53	0.02**
rv_exrate does not Granger cause rv_silvp	1.73	0.54

Notes: "**" indicates a rejection of the null hypothesis. rv_exrate, rv_goldp, rv_platp, rv_oilp, rv_paladp, rv_silvp are the realized volatility series for the exchange rate, gold, platinum, oil, palladium and silver, respectively.

Table 3.17 Regression Results for the conditional volatilities - Dependent is cv_exrate

Variable	Coefficient	t-statistic	p-value
constant	-1.97	-3.62	0.00***
cv_goldp	0.17	3.67	0.00***
cv_platp	0.03	0.72	0.47
cv_palladp	0.11	4.56	0.00***
cv_oilp	0.10	1.76	0.04**
cv_silvp	0.13	1.27	0.10
Adjusted R-squared			0.33
Number of Observations			280

Notes: "*", "**", "***" indicate statistical significance at 10%, 5% and 1%, respectively. cv_exrate, cv_goldp, cv_platp, cv_oilp, cv_palladp and cv_silvp are the conditional volatilities for the return on the exchange rate, gold, platinum, oil, palladium, and silver.

Table 3.18 Regression Results for the realized volatilities - Dependent variable is rv_exrate

Variable	Coefficient	t-statistic	p-value
constant	1,81	0.82	0.410
rv_goldp	0.17	3.29	0.00**
rv_platp	0.01	0.14	0.89
rv_palladp	0.04	2.41	0.02*
rv_oilp	0.06	4.02	0.00**
rv_silvp	0.03	1.61	0.11
Adjusted R-squared			0.27
Number of Observations			280

Notes: "*", **" and "***" indicate significance at 10%, 5% and 1% significance levels, respectively. rv_exrate, rv_goldp, rv_platp, rv_oilp, rv_paladp, rv_silvp are the realized volatility series for the exchange rate, gold, platinum, oil, palladium and silver, respectively.

Table 3.19 Overall OLS and Exclusion Test

	Conditional Volatility		Realized Volatility	
	Coefficient	Exclusion Test	Coefficient	Exclusion Test
σ^2_{goldp}	0.21	5.48*	0.19	5.70*
σ^2_{platp}	0.06	1.25	0.06	1.68
$\sigma^2_{palladp}$	0.06	2.57*	0.07	3.71*
σ^2_{oilp}	0.12	8.58*	0.11	12.55*
σ^2_{silvp}	0.07	1.15	0.07	1.84

Notes: The exclusion test is an F-test where the unrestricted model has seven lags of each volatility in commodity prices and the restricted model eliminates the effect of volatility of each commodity price one at a time. "*" indicates rejection of the null hypothesis. The critical values for the F-test are 2.51 and 1.94 for 1% and 5% Significance level.

Table 3.20 Variance Decomposition of for model A – Realized Volatility

Variance Decomposition of volatility in gold prices (rv_goldp)		
Period	rv_goldp	rv_exrate
1	100	0.00
2	99.42	0.58
3	98.75	1.25
6	97.68	2.32
12	97.42	2.58
24	97.41	2.59
Variance Decomposition of volatility in exchange rate (rv_exrate)		
Period	rv_goldp	rv_exrate
1	3.71	96.29
2	9.36	90.64
3	13.82	86.18
6	19.54	80.46
12	20.79	79.21
24	20.82	79.18

Notes: The Cholesky ordering is (rv_goldp, rv_exrate)

Table 3.21 Variance Decomposition of for model B – Realized Volatility

Variance Decomposition of volatility in platinum prices (rv_platp)		
Period	rv_platp	rv_exrate
1	100	0.00
2	99.48	0.52
3	98.86	1.14
6	97.94	2.06
12	97.77	2.23
24	97.77	2.24
Variance Decomposition of volatility in exchange rate (rv_exrate)		
Period	rv_platp	rv_exrate
1	3.54	96.46
2	6.18	93.82
3	8.03	91.97
6	10.13	89.87
12	10.48	89.52
24	10.48	89.52

Notes: The Cholesky ordering is (rv_platp, rv_exrate)

Table 3.22 Variance Decomposition of for model C – Realized Volatility

Variance Decomposition of volatility in palladium prices (rv_palladp)		
Period	rv_palladp	rv_exrate
1	100	0.00
2	99.76	0.24
3	99.47	0.53
6	99.05	0.95
12	98.98	1.02
24	98.98	1.02
Variance Decomposition of volatility in exchange rate (rv_exrate)		
Period	rv_palladp	rv_exrate
1	5.78	94.22
2	9.77	90.23
3	12.47	87.53
6	15.42	84.58
12	15.86	84.14
24	15.87	84.13

Notes: The Cholesky ordering is (rv_palladium, rv_exrate)

Table 3.23 Variance Decomposition of for model D – Realized Volatility

Variance Decomposition of volatility in oil prices (rv_oilp)		
Period	rv_oilp	rv_exrate
1	100	0.00
2	99.00	1.00
3	97.94	2.06
6	96.58	3.42
12	96.35	3.65
24	96.35	3.65
Variance Decomposition of volatility in exchange rate (rv_exrate)		
Period	rv_oilp	rv_exrate
1	3.54	96.46
2	7.92	92.08
3	10.83	89.17
6	13.82	86.18
12	14.27	85.73
24	14.28	85.72

Notes: The Cholesky ordering is (rv_oilp, rv_exrate)

Table 3.24 Variance Decomposition of for model E – Realized Volatility

Variance Decomposition of volatility in silver prices (rv_silvp)		
Period	rv_silvp	rv_exrate
1	100	0.00
2	99.70	0.30
3	99.34	0.66
6	98.76	1.24
12	98.63	1.37
24	98.63	1.37
Variance Decomposition of volatility in exchange rate (rv_exrate)		
Period	rv_silvp	rv_exrate
1	2.47	97.53
2	7.05	92.95
3	10.77	89.23
6	15.52	84.48
12	16.46	83.54
24	16.48	83.52

Notes: The Cholesky ordering is (rv_silvp, rv_exrate)

Table 3.25 Variance Decomposition of for model A - Conditional Volatility

Variance Decomposition of volatility in gold prices (cv_goldp)		
Period	cv_goldp	cv_exrate
1	100	0.00
2	93.95	6.05
3	91.26	8.74
6	88.82	11.18
12	88.05	11.95
24	87.95	12.05
Variance Decomposition of volatility in exchange rate (cv_exrate)		
Period	cv_goldp	cv_exrate
1	8.78	91.22
2	12.55	87.45
3	15.06	84.94
6	18.75	81.25
12	20.49	79.51
24	20.75	79.25

Notes: The Cholesky ordering is (cv_goldp, cv_exrate)

Table 3.26 Variance Decomposition of for model B – Conditional Volatility

Variance Decomposition of volatility in platinum prices (cv_platp)		
Period	cv_platp	cv_exrate
1	100	0.00
2	99.18	0.82
3	99.01	0.99
6	98.98	1.02
12	98.98	1.02
24	98.98	1.02
Variance Decomposition of volatility in exchange rate (cv_exrate)		
Period	cv_platp	cv_exrate
1	4.67	95.33
2	9.21	90.79
3	11.00	89.00
6	11.79	88.21
12	11.81	88.19
24	11.81	88.19

Notes: The Cholesky ordering is (cv_platp, cv_exrate)

Table 3.27 Variance Decomposition of for model C – Conditional Volatility

Variance Decomposition of volatility in palladium prices (cv_palladp)		
Period	cv_palladp	cv_exrate
1	100	0
2	99.82	0.18
3	99.72	0.28
6	99.64	0.36
12	99.63	0.37
24	99.63	0.37
Variance Decomposition of volatility in exchange rate (cv_exrate)		
Period	cv_palladp	cv_exrate
1	7.62	92.38
2	12.64	87.36
3	15.20	84.80
6	17.02	82.98
12	17.17	82.83
24	17.18	82.82

Notes: The Cholesky ordering is (cv_goldp, cv_exrate)

Table 3.28 Variance Decomposition of for model D – Conditional Volatility

Variance Decomposition of volatility in oil prices (cv_oilp)		
Period	cv_oilp	cv_exrate
1	100	0.00
2	99.84	0.16
3	99.56	0.44
6	98.53	1.47
12	97.00	3.00
24	95.91	4.09
Variance Decomposition of volatility in exchange rate (cv_exrate)		
Period	cv_oilp	cv_exrate
1	4.03	95.97
2	4.98	95.02
3	5.96	94.04
6	8.87	91.13
12	13.21	86.79
24	16.79	83.21

Notes: The Cholesky ordering is (cv_goldp, cv_exrate)

Table 3.29 Variance Decomposition of for model E – Conditional Volatility

Variance Decomposition of volatility in silver prices (cv_silvp)		
Period	cv_silvp	cv_exrate
1	100	0
2	99.98	0.02
3	99.96	0.04
6	99.92	0.08
12	99.87	0.13
24	99.84	0.16
Variance Decomposition of volatility in exchange rate (cv_exrate)		
Period	cv_silvp	cv_exrate
1	0.43	99.57
2	1.31	98.69
3	2.53	97.47
6	7.17	92.83
12	14.53	85.47
24	18.56	81.44

Notes: The Cholesky ordering is (cv_goldp, cv_exrate)

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