Commodity price developments and the minerals industry

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2 October 2024

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October 02, 2024

Abstract

This paper analyses the reaction of the minerals industry to Commodity price *developments* in South Africa. This is achieved by augmenting a Taylor (1993) rule type central bank monetary policy reaction function with a measure of commodity prices. The results provide evidence of a statistically significant effect of an increase in commodity prices on output of the mining industry, which peaks at 0.69 percentage points after 3 months, with statistically significant impact that lasts up to 5 months. This is consistent with the hypothesis that the prices of Commodities and economic growth co move in the short run, while the large and persistent movements in commodity prices exhibit no such changes in economic growth, particularly in most resource rich countries. The results have also shown that the effect of the increase in output of minerals industry on commodity prices is, however, statistically insignificant in all periods, which implies inadequate market share of the minerals industry in commodities markets. The results support the hypothesis of a transitory comovement of the prices of commodities and output of the minerals industry, hence policy makers and mining authorities should continue to monitor developments in commodity prices to support overall economic activity as well as the minerals industry.

JEL Classification:C10, E50, L70, L72
Keywords: commodity prices, Minerals industry, Economic cycles

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Introduction

Commodity prices have undergone repeated cycles over the past century. These repeated cycles, referred to as the boom and bust cycles, have important implications for global macroeconomic fluctuations, affecting the goods and services markets and financial markets etc., as evidenced in Labys et al. (1999), Labys and Maizels (1993) and Frankel (2008). As with equity securities, commodity prices are primarily determined by the forces of supply and demand, including cost of production, currency Movements, geopolitical events, natural disasters, speculative trading, government policies and more, in commodities markets. Commodity markets, typically natural resources, including energy, metals and minerals, as well as agricultural products, help to determine the prices of the raw materials that are essential for most product markets. Commodity prices rose sharply since 2000, peaking in 2008 as well as in 2020, consistent with the onset of the Global financial crisis and the Covid 19 pandemic. According to Blanchard and Gali (2007) and Frankel (2010), explanations for the elevated commodity prices include strong global growth, easy monetary policy, speculative bubbles and market risk.

Evidence shows that economies, particularly those that are abundantly endowed with natural resources and hence are dependent on commodity exports, have a long history of volatile and disruptive economic cycles, as summarised in Frankel (2010), Frankel (2012) and Jacks (2013). South Africa's mining sector was the second most important industry in the 1970s and 1980s, with more than 20 percent contribution to the Gross Domestic Product (GDP). Meanwhile, the sector currently accounts for single digit figure to the economy in the recent decades. The South African minerals industry output stagnated in real terms, while it has declined progressively as a percentage of Gross Domestic product (GDP), in recent decades. Paradoxically, the aggregate economy has been growing at rates of

about 4 percent between 2000 and 2010 as well as at rates of below 2 percent, on average, since then. According to Government Communication and Information System (GCIS), South Africa is known for its abundance of mineral resources and is estimated to have the world's fifth largest mining sector, while its mining companies are key players in the global industry. A phenomenon where countries fail to convert natural resource wealth into superior economic performance is referred to as the Natural Resource Curse, resulting in the Dutch Disease, as discussed in Van Wijnbergen (1984), Auty (2002), Auty (2005), Kaminsky et al. (2004), Spatafora and Tytell (2009), Frankel (2010) and Frankel (2012).

Conventional macroeconomic models distinguish between alternative "anchors" to stabilise the cyclical behavior of economic activity. Macroeconomics literature further highlights the importance of the different shocks, that include the demand and supply side shocks, market rigidities as well as investor and consumer sentiments, while it also emphasises the effects of these shocks during the different phases and components of the economy. According to Blanchard et al. (1986), Shapiro (1987), Blanchard and Quah (1988), Shapiro and Watson (1988), Quah (1988), Kydland and Prescott (1990), Gali (1992) and Romer (1993) the short term, or transitory, economic fluctuations are determined by demand shocks while the long term, or permanent, economic fluctuations are determined by supply shocks. For instance, whereas monetary and fiscal policies are typical demand side management anchors, fiscal policy can also be a supply side management anchor, while the changes in commodity prices also demonstrate this demand and supply side disturbances to the economy. Consequently, Diebold and Rudebusch (1970) and Romer (1993) argue that the different economic sectors respond differently to endogenous and exogenous economic shocks as well as the long run and short run disturbances.

The short term, or transitory, economic fluctuations emanate from changes in monetary, financial and fiscal policies as well as consumer and business sentiment, according to Blanchard et al. (1986), Shapiro (1987), Blanchard and Quah (1988), Shapiro and Watson (1988), Quah (1988) and Gali (1992). The long term, or permanent, economic fluctuations emanate from the nominal rigidities that include changes in technological advancement, privatisation, deregulation as well as multilateral agreements. The short term economic fluctuations are, therefore, determined by demand side shocks, while long term economic fluctuations are determined by the supply side shocks. Demand side and supply side economic management paradigm suggest the need to decompose the macroecomomic indicators into their transitory and permanent components. A detailed literature on the isolation of macroeconomic variables into the short and long run components can be found in Kydland and Prescott (1990), Romer (1993) and Stock and Watson (1999). Hodrick and Prescott (1997), Baxter and King (1999) and Christiano and Fitzgerald (2003), as will be discussed, provide the methodological approaches.

This paper analyses the reaction of the minerals industry to Commodity price *developments* in South Africa. This is achieved by augmenting a Taylor (1993) rule type central bank monetary policy reaction function with a measure of commodity prices. Understanding the reaction of the minerals industry to commodity price *developments* over the economic cycle is important to mining authorities and policymakers alike. For instance, the comovement, or divergence, of the fluctuations of different economic sectors and industries, as with the minerals industry, could be because they behave differently to the common endogenous and exogenous shocks. As opposed to the macroeconomics literature, according to the European Central Bank (ECB) (2012) and Morgan Stanley Capital International (MSCI). (2014), the investment literature distinguishes between types of industries, categorised into defensive, cyclical and sensitive industries, based on how they respond to economic fluctuations over the economic cycle. Spatafora and Tytell (2009) argue that the connection between commodity prices and macroeconomic performance has been hotly debated in macroeconomics, with some studies finding that commodity markets booms advance economic growth, while other studies suggest the Natural Resource Curse, culminating in the Dutch Disease, that undermine sustainable economic growth.

The paper is organised as follows. The next section discusses the data. This is followed by the specification of the model and the estimation technique. The subsequent section reports the empirical results and last is the conclusion, together with recommendations and areas of further research.

Data

Monthly data spanning the period January 2000 to December 2023 is used to analyse the reaction of the minerals industry to commodity price *developments*. The variables comprise mining and quarrying output, inflation rate, monetary policy interest rate and commodity prices. Mining output is Gross Value Added (GVA) of the mining and quarrying, or the minerals industry. Inflation rate, or the change in annual Consumer Price Index (CPI), is the annual headline consumer price inflation. Monetary

policy interest rate, or central bank interest rate, is the short term policy rate, also called repurchase rate, and is the rate at which private sector banks borrow from the central bank. Commodity prices is the All Commodity Price Index, includes the prices of energy, metals and minerals, agriculture and other commodities. The data on mining output and inflation rate was sourced from Statistics South Africa, the data on the interest rate was sourced from the South African Reserve Bank, while the data on commodity prices was sourced from World Bank (WB) Commodity Price Data, or the Pink Sheet. The descriptions and sources of the variables are presented in Table 1. Mining and quarrying output is denoted $GVAMng$, inflation rate, is denoted $CPIRate$, central bank monetary policy interest rate, is denoted $CBRate$, while $COMPrice$ denotes commodity prices.

Variable	Denotation	Description
Mining output	GVAMng	Gross Value Added (GVA) of the mining and quarrying, or minerals, industry
Inflation rate	CPIRate	Inflation rate, or annual Consumer Price Index (CPI), is the annual headline consumer price inflation
Interest rate	CBRate	Central bank policy rate and is the rate at which private sector banks borrow from the central bank
Commodity prices	COMPrice	All Commodity Price Index, includes energy, metals and minerals, agriculture and prices of other commodities

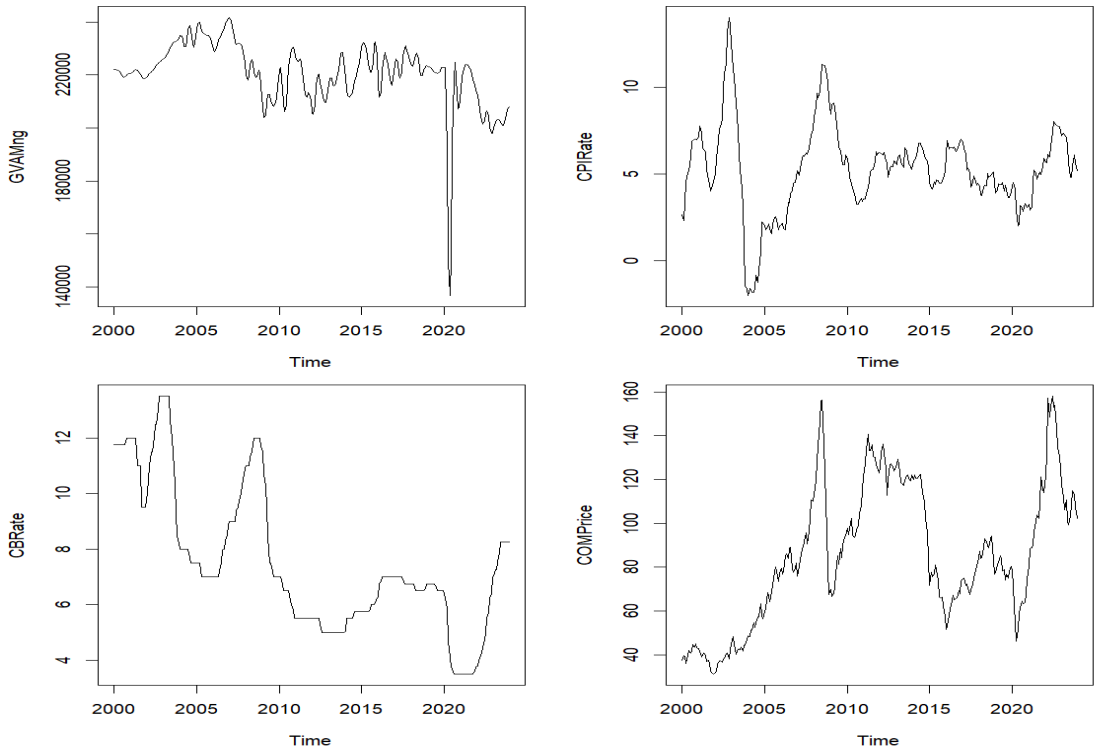
Notes: Data sourced from Statistics South Africa, South African Reserve Bank and the World Bank. Mining and quarrying output is denoted $GVAMng$, consumer price inflation rate, is denoted CPI, central bank monetary policy interest rate, is denoted $CBRate$ and $COMPrice$ denotes commodity prices.

Table 1: Description of variables

The evolution of the variables are depicted in Figure 1. Output of the mining and quarrying industry increased between 2003 and 2007, where it reached a peak, and decreased significantly to 2009. The decrease in output of the mining and quarrying was due to the onset of the Global financial crisis in late 2008. Output of the mining and quarrying industry then increased, albeit volatile, from 2010 to 2015 where it subsequently decreased from 2016 to 2023, and more so in 2022 and 2023. The significant decrease in output of the mining and quarrying in 2020 was due to the onset of the Covid 19 pandemic. Inflation rate, or the change in annual Consumer Price Index (CPI), increased from 2000 and reached a peak in 2003 where it decreased significantly and bottomed in 2004. Inflation rate increased again between 2005 and 2008 before it decreased between 2009 and 2011. The indicator then remained range bound but volatile between 2012 and 2021 where it then spiked in in 2022 before decreasing in 2023. The movements of the central bank monetary policy interest rate closely mirrored the movements in inflation rate during the sample period between 2000 and 2023. However, the interest rate, which is the rate at which private sector banks borrow from the central bank, was generally in a down ward trend between 2000 and 2023 with notable spikes and peaks in 2003, 2008 and 2003, while the opposite is true in 2005, 2013 as well as in 2021. The central bank interest rate increased substantially from early 2022 to counteract the rising consumer price inflation in the same period.

Commodity prices maintained an upward trend, on average, between 2000 and 2023, or throughout the sample period, albeit volatile. Although commodity prices were increasing since 2000, they accelerated notably from 2002, peaking in 2008. The decrease witnessed in 2009 was followed by another significant increase in 2010 and 2011. Commodity prices subseqently decreased, on average, from 2012 and bottomed out in 2016 and 2020. Another significant increase in commodity prices was realised from 2021 with a peak in 2022, before they decreased again in 2023. The fluctuations in commodity prices were erratic and inconsistent indicating volatile demand and supply conditions in commodities markets. The peaks in commodity prices in 2008, 2011 and 2021 coincide with the onset of the Global financial crisis, sovereign debt crisis as well as Covid 19 pandemic. Commodity price volatility induces significant terms of trade shocks with adverse impact on economic agents, government policies and economic growth, especially for countries that export commodities. Frankel (2008), Spatafora and Tytell (2009) and Stuermer (2018) discusses the century long behavior of prices in commodities markets.

The variables were transformed to the deviation from their Hodrick and Prescott (1997) trends. 24 months were forecasted at the end of each variable series to correct the Hodrick and Prescott (1997)



Notes: Data sourced from Statistics South Africa, South African Reserve Bank and the World Bank. Mining and quarrying output is denoted $GVAMng$, consumer price inflation rate, is denoted CPI, central bank monetary policy interest rate, is denoted $CBRate$ and $COMPrice$ denotes commodity prices. The x axis depicts the time period.

Figure 1: Plots of the variables

trend end point problem following Ravn and Uhlig (2002) and Mise et al. (2005). Dating the phases of the economic time series as well as decomposing the economic time series into its short run and long run components are discussed in Burns and Mitchell (1946), Friedman et al. (1963), Romer (1986), Gordon (2007), Kydland and Prescott (1990), Romer (1993) and Stock and Watson (1999), while Hodrick and Prescott (1997), Christiano and Fitzgerald (2003) as well as Baxter and King (1999) provide the methodological aspects of decomposing the economic time series into its components. Decomposing the economic time series into its unobserved short term, also called cyclical, as well as long term, also called permanent or trend, components, will facilitate the analysis of the reaction of mining and quarrying, or the minerals industry, to foreign exchange *developments* over the economic cycle.

Methodology

A Vector Autoregression (VAR) model is estimated to capture the relationship between the minerals industry and commodity price developments. The specified Vector Autoregression (VAR) model follows Stock and Watson (2001) and Kadiyala and Karlsson (1997). Vector Autoregression (VAR) models were introduced in applied macroeconomic research by Sims (1980), while the early contributions to their Bayesian equivalents include Litterman (1984). According to Stock and Watson (2001) and Rudebusch (1998), a Vector Autoregression (VAR) is a system of linear equations, one for each variable in the system. In reduced form, each equation in a Vector Autoregression (VAR) model specifies one of the variables as a linear function of its own lagged values as well as the lagged values of other variables being considered in the system and a serially uncorrelated error term. In general, for a VAR(p) model, the first p lags of each variable in the system are used as the regression predictors for each variable.

Vector Autoregression (VAR) models have become standard tools in macroeconomics structural analysis and forecasting, as argue Giannone et al. (2010), Koop and Korobilis (2010) and Koop (2013). According to Del Negro and Schorfheide (2011), these models can capture the important stylised facts about the economic time series despite their simple formulation. These include the decaying pattern in

the values of the autocorrelations as the lag order increases and the dynamic linear interdependencies between the model variables. A Vector Autoregression (VAR) model is specified as follows

$$Y_t = \delta + \theta_1 Y_{t-1} + ... + \theta_p Y_{t-p} + \epsilon_t \tag{1}$$

where $Y_t = (Y_{1,t}, ..., Y_{n,t})$ is the $n * 1$ is vector of random variables observed at time t. $\delta = (\delta_1, ..., \delta_n)$ is the $n * 1$ vector of constants or intercept terms, $\theta_1, ..., \theta_p$ are $n * n$ matrices of coefficients, p is the number of lags of each of the n variables and $\epsilon_t = (\epsilon_{1,t}, ..., \epsilon_{n,t})$ is the $n * 1$ dimensional vector of white noise error terms denoted

$$\epsilon_t \sim N(0, \Sigma) \tag{2}$$

where Σ is the $n * n$ variance covariance matrix. Evans and Kuttner (1998), Rudebusch (1998) and Stock and Watson (2001) argue that the error terms are the unanticipated policy shocks, or the surprise movements, after taking into account the past values of the Vector Autoregression (VAR) model.

A general matrix notation of a Vector Autoregression (VAR) model with p number of lags, or VAR(p), and no deterministic regressors, can be written as

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \\ \vdots \\ Y_{n,t} \end{bmatrix} = \begin{bmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_n \end{bmatrix} + \begin{bmatrix} \theta_{1,1} & \theta_{1,2} & \cdots & \theta_{1,n} \\ \theta_{2,1} & \theta_{2,2} & \cdots & \theta_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{n,1} & \theta_{n,2} & \cdots & \theta_{n,n} \end{bmatrix} \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ \vdots \\ Y_{n,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \vdots \\ \epsilon_{n,t} \end{bmatrix} \tag{3}$$

where in this instance, p, or the number of lags, is equal to 1 for each of the n variables. A detailed discussion on Vector Autoregression (VAR) models can be found in Hamilton (1994), while recent contributions include Lütkepohl (2005), Koop and Korobilis (2010) and Giannone et al. (2015).

A Vector Autoregression (VAR) model is estimated using Bayesian methods. A Minnesota prior is specified and a Gibbs style sampler is used in estimation following Kadiyala and Karlsson (1997). At the heart of Bayesian analysis is the Bayes theorem and it is specified as

$$P(\theta_i, \Sigma \mid Y_t, M_i) P(Y_t \mid \Sigma, M_i) = P(Y_t \mid \theta_i, \Sigma, M_i) P(\theta_i, \Sigma \mid M_i) \tag{4}$$

where M_i is an arbitrary model among a general class of models, θ_i is the parameter vector described above, $p(\theta_i \mid Y_t, M_i)$ is the posterior model probability, $p(Y_t \mid \theta_i, M_i)$ is the marginal likelihood of the model, $p(\theta_i \mid M_i)$ is the prior model probability and $p(Y_t \mid M_i)$ is the constant integrated likelihood over all models. The details on a Bayesian Vector Autoregression (BVAR) model estimation with Minnesota prior, first introduced by Litterman (1979), Litterman (1980) and Litterman (1984) and developed by Sims (1989), is used in this paper, while a brief introduction to Bayesian econometrics and Bayesian Vector Autoregression models, can be found in O'Hara (2015). A more general treatment of Vector Autoregression (VAR) models, including Bayesian estimation with the different types of model priors, can be found in Koop and Korobilis (2010), Canova (2011) as well as Giannone et al. (2015).

According to Rudebusch (1998), the appeal of using Vector Autoregression (VAR) models for analysing policy reaction functions is that they have the ability to identify the effects of shocks without a need to specify a complete structural model of the economy. Giannone et al. (2010) contend that Vector Autoregression (VAR) models have become popular among empirical macroeconomists because they facilitate insight into the dynamic relationships between the economic variables in a relatively unconstrained manner. Koop and Korobilis (2010) and Koop (2013) further argue that the Bayesian methods have become an increasingly popular way of dealing with the problem of over parameterisation of economic models given the limited length of standard macroeconomic datasets. Vector Autoregression (VAR) models can be used successfully in macroeconomic forecasting with a large number of variables when coupled with Bayesian estimation, as argue Sims and Uhlig (1991), due to the flexibility provided by the application of the Bayesian parameter shrinkage. Sims and Uhlig (1991) further argue that Bayesian versions of these models can incorporate unit root nonstationary variables with negligible disadvantageous influence on the inference of the parameters of the model.

Results

Bayesian Vector Autoregression (BVAR) model was estimated to capture the relationships between the minerals industry and commodity price developments, as discussed. The estimated Bayesian Vector

Autoregression (BVAR) specifies a Minnesota prior and uses a Gibbs style sampler following Stock and Watson (2001) and O'Hara (2015). The 0.05 prior was set on all coefficients except the own first lags which were set to 0.95 to account for persistence in the variables. The number of lags to include of each variable was set to 4 following the Schwarz (1978) Bayesian information criterion. The integer value for the horizon of the Impulse Response Functions (IRFs) was set to 24, corresponding to 2 years, given that monthly data is used in estimation. 10000 is the number of Gibbs sampler replications to keep from the sampling run, while 1000 is the sampling burn in length for the Gibbs sampler. Gibbs sampling, or Gibbs sampler, is a Markov Chain Monte Carlo (MCMC) technique used to sample from probability distributions, where the Gibbs sampler draws iteratively from the posterior conditional probability distributions, as alternative to sampling from a joint posterior probability distribution.

As discussed, conventional macroeconomic models distinguish between alternative "anchors" to stabilise the cyclical behavior of economic activity. Macroeconomics literature further highlights the importance of demand side and supply side shocks, market rigidities as well as investor and consumer sentiments. Evidence shows that economies, particularly those that are abundantly endowed with natural resources and hence are dependent on commodity exports, have a long history of volatile and disruptive economic cycles, as summarised in Frankel (2010), Frankel (2012) and Jacks (2013). A Taylor (1993) rule type central bank monetary policy reaction function with the output of mining and quarrying industry is, thus, augmented with a measure of commodity prices as follows

$$i_t = \rho + \theta_\pi(\pi_t - \pi_t^*) + \theta_Y(Y_t - \bar{Y_t}) + \theta_C(C_t - \bar{C_t}) + \epsilon_t \tag{5}$$

where i_t is the nominal interest rate, ρ is the natural rate of interest, π_t is the inflation rate, π_t^* is the central bank target for inflation, Y_t is output, $\bar{Y_t}$ is the natural rate of output, C_t denotes commodity prices, while $\bar{G_t}$ is the natural rate of commodity prices. θ_π, θ_Y and θ_C are the responsiveness of the nominal interest rate to the deviations of inflation from the central bank inflation target, the deviations of output from its natural rate and the deviations of commodity prices from its natural rate, respectively. ϵ_t is the error term and the subscript t denotes the time period. The central bank monetary policy reaction function captures the process through which monetary policy decisions affect consumer price inflation in particular and the aggregate economy in general. The specified central bank monetary policy reaction function ensures market clearing, or equillibrium, condition, in that when output equals its steady state level, inflation is the same as its target rate and commodity prices equal their steady state level, hence the nominal interest rate is also equivalent to its natural rate.

The variables in the specified central bank monetary policy reaction function comprise output of mining and quarrying, denoted $GVAMng_t$, inflation, denoted CPI_t, interest rate, denoted $CBRate_t$ and commodity prices, denoted $COMPrice_t$. Y_t in Equation 1 can, thus, be rewritten as

$$Y_t = (GVAMng_t, CPI_t, CBRate_t, COMPrice_t) \tag{6}$$

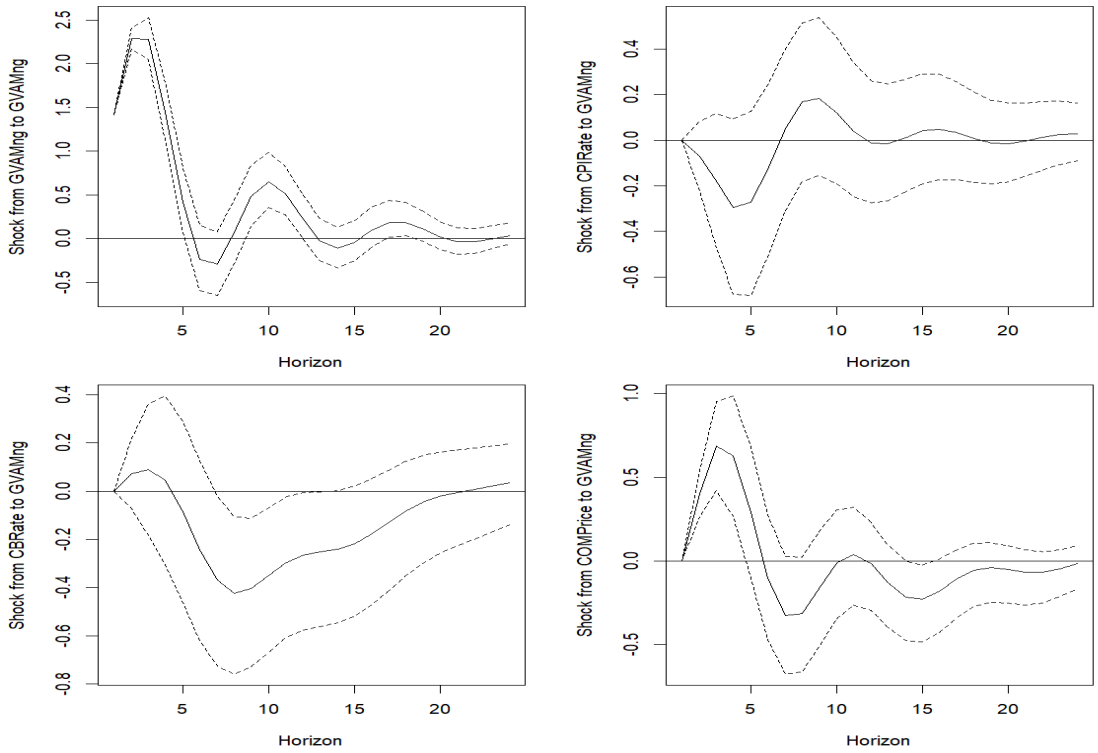
where Y_t is the vector of random variables observed at time t. Stock and Watson (2001) argue that a reduced form Vector Autoregression (VAR), on the one hand, expresses each variable as a linear function of its own past values, the past values of all other variables being considered and a serially uncorrelated error term. On the other hand, a recursive Vector Autoregression (VAR) constructs the error terms in each regression equation to be uncorrelated with the error in the preceding equations by including contemporaneous values as regressors. Consequently, the results of a recursive Vector Autoregression (VAR) depend on the order of the variables where changing the order of the model variables also changes the equations, coefficients and residuals of the Vector Autoregression (VAR).

According to Stock and Watson (2001), the standard practice in Vector Autoregression (VAR) model analysis is to report the results from Impulse Response Functions (IRFs) and Forecast Error Variance Decompositions (FEVDs). The reason is that these statistics are more informative than the estimated Vector Autoregression (VAR) regression coefficients. Rudebusch (1998) further argues that most Vector Autoregression (VAR) model equations do not have a clear structural interpretation. Vector Autoregression (VAR) models are also atheoretical, that is, they are not built on some economic theory, hence a theoretical structure is not imposed on the equations. Every variable is assumed to influence every other variable in the system, which makes a direct interpretation of the estimated coefficients difficult, according to Hyndman and Athanasopoulos (2018). Therefore, in this paper, the Impulse Response Functions (IRFs) are the only model statistics that are reported given that the interest is to analyse the reaction of the minerals industry output to commodity price developments.

The variables were transformed to stationarity in that they were decomposed into deviations from their long term trends. The detrending is useful conceptually because it eliminates the common

steering force that time may have on each variable series and hence induces stationarity. As such, the variables are mean reverting, thus, the Bayesian Vector Autoregression (BVAR) model is assumed to be covariance stationary. As discussed above, Rudebusch (1998) and Stock and Watson (2001) argue that the residuals of the Vector Autoregression (VAR) model are unanticipated shocks, or surprise movements in the variables. According to Stock and Watson (2001), the Impulse Response Functions (IRFs) trace out the response of current and future values of each of the variables to a unit increase in the current value of one of the Vector Autoregression (VAR) errors. This error is assumed to return to zero in subsequent periods and that all other errors are equal to zero. Consequently, the Impulse Response Functions (IRFs) show the impact, or effect, of a unit, or 1 percentage point, change in the variable under consideration on the rest of the other Vector Autoregression (VAR) model variables.

Impulse Response Functions (IRFs) of the Vector Autoregression (VAR) model for the reaction of the minerals industry output to innovations, or shocks, in the other variables are depicted in Figure 2, together with their 95 percent confidence intervals, or bands. According to the results, following an unexpected 1 percentage point increase in output of the minerals industry, minerals industry output initially increases and peaks at 2.28 percentage points after 3 months. The increase is followed by a rapid decrease where the minerals industry output bottoms out at -0.29 percentage points after 7 months. The initial increase in minerals industry output remains statistically significant for about 12 months following which its potency, or momentum, begins to progressively wane, or dissipate. Output of the minerals industry, thereafter, rapidly moves towards its steady state level in about 20 months. Following an unexpected 1 percentage point increase in consumer price inflation, the minerals industry output initially decreases and bottoms out at -0.29 percentage points after 4 months. Output of the minerals industry then increases, peaking at 0.18 percentage points after 9 months. Output of the Minerals industry then fluctuates around, and progressively tends towards, its natural rate. The surprise increase in consumer price inflation is, however, statistically insignificant in all periods.



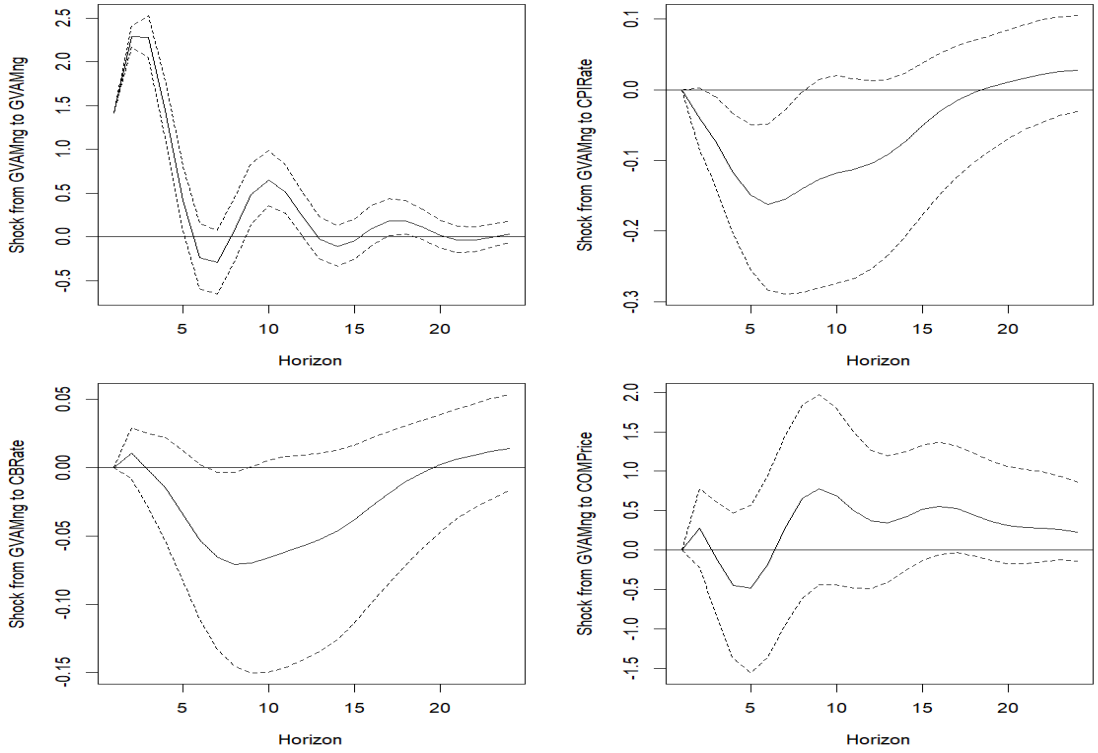
Notes: Data sourced from Statistics South Africa, South African Reserve Bank and the World Bank. Mining and quarrying output is denoted $GVAMng$, consumer price inflation rate, is denoted CPI, central bank monetary policy interest rate, is denoted $CBRate$ and $COMPrice$ denotes commodity prices. The x axis depicts the horizon of the Impulse Response Functions (IRFs).

Figure 2: Impulse Response Functions (IRFs) with shocks to output of the minerals industry

Following an unexpected 1 percentage point increase in monetary policy interest rate, output of the minerals industry increases slightly and peaks after 3 months. The initial increase in output

of the minerals industry is followed by a decrease where the minerals industry output bottoms out at -0.42 percentage points after 8 months. The effect of the surprise increase in monetary policy interest rate is, however, statistically significant between 6 and 14 periods, following which it begins to progressively discipate and hence the minerals industry output gradually tends towards its steady state level. Following an unexpected 1 percentage point increase in commodity prices, output of the minerals industry initially increases and peaks at 0.69 percentage points after 3 months. The initial increase is followed by the decrease and where output of the minerals industry bottoms out at -0.33 percentage points after 7 months. The decrease in output of the minerals industry is subsequently followed by a stable fluctuation and gradual increase of output of the minerals industry towards its equilibrium, or steady state, level after 24 months. The effect of an unexpected, or surprise, increase in commodity prices on output of mining and quarrying is statistically significant up to 5 months.

Impulse Response Functions (IRFs) of the Vector Autoregression (VAR) model with innovations, or shocks, in the minerals industry output are depicted in Figure 3, together with their 95 percent confidence intervals, or bands. The results of the reaction of the minerals industry output to its own innovations, or to an unexpected 1 percentage point increase in minerals industry output, are reported above. Following an unexpected 1 percentage point increase in output of the minerals industry, consumer price inflation decreases and bottoms out at -0.16 percentage points after 8 months. Consumer price inflation subsequently increases progressively, tends towards and fluctuates around, its equilibrium, or steady state, level in about 19 months. The effect of the surprise increase in output of the minerals industry on consumer price inflation is statistically significant between 3 and 8 months.



Notes: Data sourced from Statistics South Africa, South African Reserve Bank and the World Bank. Mining and quarrying output is denoted $GVAMng$, consumer price inflation rate, is denoted CPI, central bank monetary policy interest rate, is denoted $CBRate$ and $COMPrice$ denotes commodity prices. The x axis depicts the horizon of the Impulse Response Functions (IRFs).

Figure 3: Impulse Response Functions (IRFs) with shocks from output of the minerals industry

Following an unexpected 1 percentage point increase in output of the minerals industry, the central bank monetary policy interest rate initially increases, peaking at 0.01 percentage points after 2 months. Central bank monetary policy interest rate subsequently decreases and bottoms out at -0.07 percentage points after 8 months. Central bank monetary policy interest rate subsequently increases progressively, tends towards and fluctuates around, its equilibrium, or steady state, level. The effect of the surprise increase in output of the minerals industry on consumer price inflation is, however,

statistically significant between 7 and 8 months. Following an unexpected, or surprise, 1 percentage point increase in output of the minerals industry, commodity prices initially increase slightly and then decrease and bottom out at -0.47 percentage points after 5 months. Commodity prices subsequently recover and peak at 0.76 percentage points after 9 months before it progressively, tends towards and fluctuates around, its equilibrium, or steady state, level. The effect of the unexpected increase in output of mining and quarrying on commodity prices is, however, statistically insignificant in all periods.

The boom and bust cycles in prices of commodities, as discussed, have had important implications for global macroeconomics fluctuations, affecting everything from the goods and services markets to financial markets, as evidenced in Labys et al. (1999), Labys and Maizels (1993), Frankel (2008) and Blanchard and Gali (2007). The results provide evidence of a statistically significant effect of an increase in commodity prices on output of the mining industry, peaking at 0.69 percentage points after 3 months, with statistically significant impact that lasts up to 5 months. The results are consistent with the hypothesis that the prices of Commodities and economic growth co move in the short run, while large and persistent long run movements in commodity prices exhibit no such large persistent changes in economic growth, particularly in most resource rich countries. Evidence also shows that economies, particularly those that are abundantly endowed with natural resources and hence are dependent on commodity exports, have a long history of volatile and disruptive economic cycles, as summarised in Frankel (2010), Frankel (2012) and Jacks (2013). The results have also shown that the effect of the unexpected increase in output of minerals industry on commodity prices is, however, statistically insignificant in all periods. This means that the minerals industry lacks the market share to influence the market price of commodities and hence it must accept prevailing prices in commodities markets.

Commodity prices rose sharply since 2002, peaking in 2008 as well as in 2020, consistent with the onset of the Global financial crisis and the Covid 19 pandemic. However, the minerals industry output underperformed relative to the total, or economy wide, output since the 1970s. In particular, the minerals industry output which stagnated in real terms, while it has declined progressively as a percentage of Gross Domestic product (GDP), in recent decades, while in Paradox, the aggregate economy has been growing at rates of about 4 percent between 2000 and 2010 as well as at rates of below 2 percent, on average, since then. Decoupling of the minerals industry output amid the rising prices of commodities is at odd with the Government Communication and Information System (GCIS) assertion that South Africa has abundance of mineral resources and is estimated to have the world's fifth largest mining sector, while its mining companies are key players in the global industry, with the world's largest reported reserves of some important minerals. The minerals industry has not been able to convert natural resource wealth into superior economic performance, amid the commodity price boom since 2002. How commodity prices affect the macroeconomic performance, particularly in commodity exporting countries, has long been the subject of heated debate, as discussed in Van Wijnbergen (1984), Auty (2005), Auty (2002), Kaminsky et al. (2004), Spatafora and Tytell (2009), Frankel (2012) and Stuermer (2018). Evidence finds that commodity booms raise economic growth, while others suggest the Natural Resource Curse, resulting in the Dutch Disease, that undermines sustainable growth.

Conclusion

This paper analysed the reaction of the minerals industry to fiscal policy *developments* in South Africa. This was achieved by augmenting a Taylor (1993) rule type central bank monetary policy reaction function with an index of commodity prices. The results provide evidence of a statistically significant effect of an increase in commodity prices on output of the mining industry, peaking at 0.69 percentage points after 3 months, with statistically significant impact that lasts up to 5 months. This is consistent with the hypothesis that the prices of Commodities and economic growth co move in the short run, while the large and persistent movements in commodity prices exhibit no such changes in economic growth, particularly in most resource rich countries. The results have also shown that the effect of the increase in output of minerals industry on commodity prices is, however, statistically insignificant in all periods. This implies that the minerals industry has inadequate market share, or power, to influence the Global prices of commodities and hence must accept prevailing prices in commodities markets.

Although evidence shows that the increase in prices of commodities raise output of the minerals industry and hence economic growth, such increase in economic performance is short lived. Commodity prices rose sharply since 2002, however, the minerals industry output has consistently underperformed relative to the total, or economy wide, output since the 1970s. Decoupling of the minerals industry output amid the rising prices of commodities is at odd with the abundance of mineral resources with

the world's largest reported reserves in South Africa. The minerals industry has, thus, been unable to convert natural resource wealth into superior macroeconomic performance, referred to as the Natural Resource Curse, often resulting in the Dutch Disease, similar to most commodity exporting countries. Several economic indicators, such as the monetary policy interest rates, Government expenditure and taxation, prices of financial assets as well as foreign exchange rate, affect economic activity, at least theoretically, hence it's important for future research to analyse their impact on the minerals industry.

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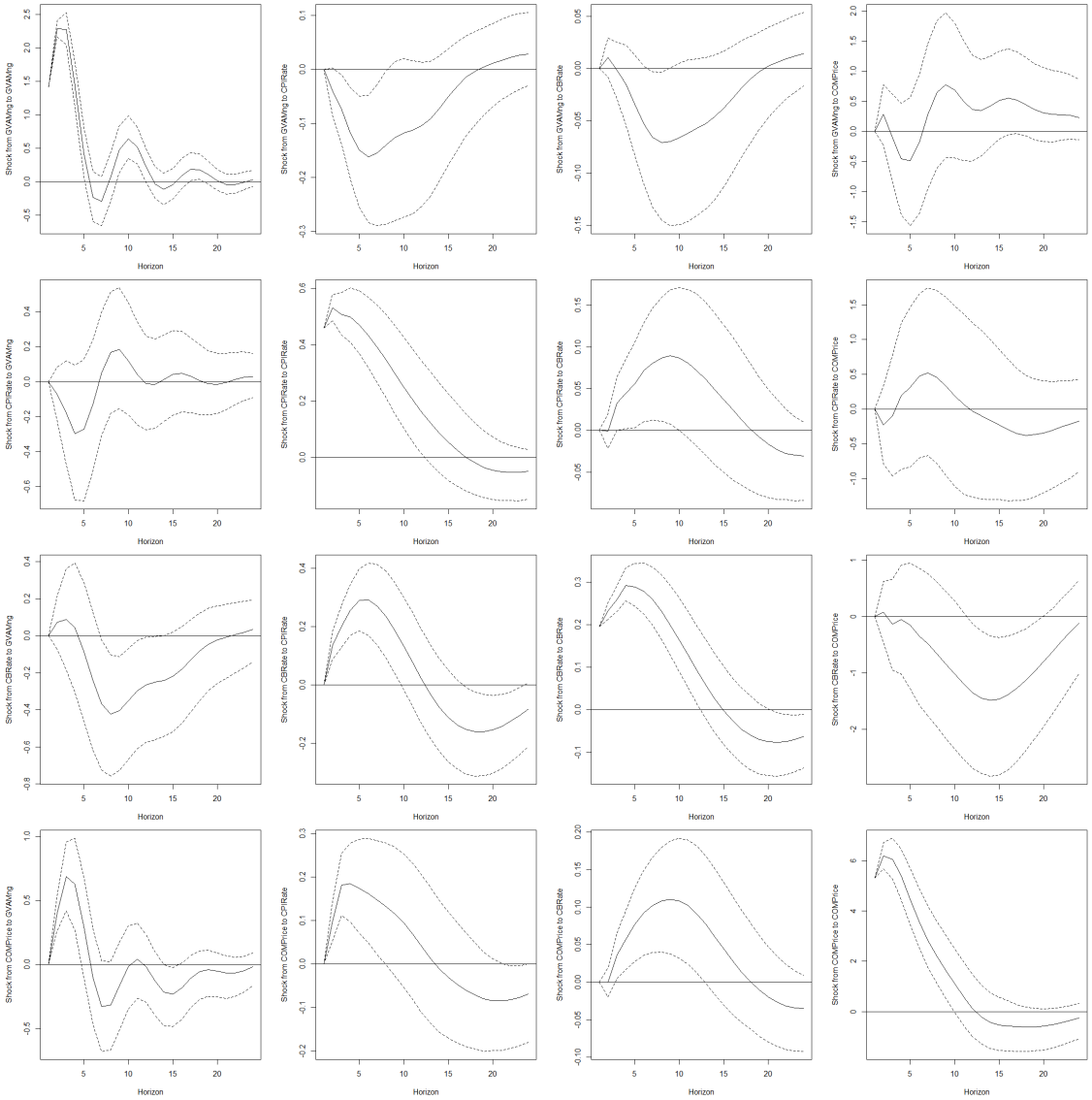
Appendix

Appendix 1. Complete Impulse Response Functions (IRFs)

The complete Impulse Response Functions (IRFs) of the Vector Autoregression (VAR) model with commodity prices are shown in Figure 4. This Figure is not intended to be a part of the paper, but is included to demonstrate the completeness of the analysis.



Notes: Data sourced from Statistics South Africa, South African Reserve Bank and the World Bank. Mining and quarrying output is denoted $GVAMng$, consumer price inflation rate, is denoted CPI, central bank monetary policy interest rate, is denoted $CBRate$ and $COMPrice$ denotes commodity prices. The x axis depicts the horizon of the Impulse Response Functions (IRFs).

Figure 4: Complete Impulse Response Functions (IRFs) with commodity prices