Market uncertainty developments and the minerals industry

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Abstract

This paper analyses the reaction of the minerals industry to market uncertainty *developments* in South Africa. This is achieved by augmenting a Taylor (1993) rule type central bank monetary policy reaction function with the Chicago Board Options Exchange's (CBOE's) Volatility Index (VIX), or market uncertainty, index. The empirical results provide evidence of a statistically significant effect of an increase in market uncertainty on output of the minerals industry, which decreases and bottoms out after 3 months, where this effect is statistically significant up to 6 months. The results further show that following an increase in output of the minerals industry, the market uncertainty index decrease slightly and bottoms out after 2 months, with a statistically significant effect up to 2 months, which indicates a weak feedback effect between market uncertainty and output of the minerals industry. Market uncertainty is, thus, important economic activity, hence policymakers should continue to monitor the developments in market uncertainty to support economic activity as well as the minerals industry.

JEL Classification:C10, E50, G10, L70
Keywords: Market uncertainty, Minerals industry, Economic cycles

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Introduction

Market uncertainty, a phenomenon where economic agents cannot contemplate the possible states of events, or characterise their probability distributions, and their outcomes until further information becomes available, has direct implications for economic activity, affecting business investment and household consumption decisions. According to Gilchrist et al. (2014), there are many sources of economic uncertainty, including changes in economic and financial policies and regulations, differing views on economic growth prospects, adverse productivity movements as well as potential wars, acts of terrorism and natural disasters. the countercyclical behavior of economic variables such as consumption, employment, income, business profits, productivity, and stock returns reflects fluctuations, or volatility, of the underlying economic shocks, or the swings in market uncertainty, according to Gilchrist et al. (2014). Empirical studies, discussed below that include Kose and Terrones (2015), Bobasu et al. (2020) as well as Gieseck and Rujin (2020), provide evidence that the recent episodes of elevated market uncertainty during the Global financial crisis, Sovereign debt crisis as well as the Covid 19 pandemic were important factors behind the weakness of global economic growth and recovery.

Quantifying market uncertainty is a challenge given that it is an unobservable, or a latent, variable and it is, thus, deduced from other variables that emphasise on distinct aspects of adverse volatility that an economy faces over time, according to Kose and Terrones (2015). Several proxies have been proposed in macroeconomics literature to approximate market uncertainty. According to the European Central Bank (ECB) (2016) and Bobasu et al. (2020), these measures include the indicators of volatility in macroeconomic and financial markets, surveys among private households and businesses, the counts of the word "economic uncertainty" in news articles and measures that are based on dispersion between professional forecasters about future economic outcomes. On Global basis, the Chicago Board Options Exchange's (CBOE's) Volatility Index (VIX), which traces its origin to Brenner and Galai (1989) and

Brenner and Galai (1993), is one of the most recognised measure of market volatility, the most widely reported in the media and the most closely followed market indicator by a variety of economic agents. Mcfarren (2013) and Edwards and Preston (2017) provide details about the methodology and rationale behind compilation of the Chicago Board Options Exchange's (CBOE's) Volatility Index (VIX).

The theoretical transmission mechanisms, or channels, on the effects of market uncertainty on economic activity include the irreversibility of investment channel, precautionary savings channel and financial frictions channel, according to Gieseck and Rujin (2020). The irreversibility of investment channel, which propounds the dampening of economic activity through postponement of business investment and employment decisions, or wait and see, is described in Bernanke (1983) and Pindyck (1990). The precausionary channel, which proposes an increase in precautionary savings and reduction in current private consumption, is described in Leland (1968). The financial frictions channel, which postulates the increase in risk premia and rising costs of financing on debt contracts, or risk aversion due to sunk, or fixed adjustment, costs, is described in Christiano et al. (2014) and Arellano et al. (2019). The business cycles literature on how market uncertainty influence economic dynamics can be found in Abel (1983), Bernanke (1983), Abel and Eberly (1994), Abel and Eberly (1996), Caballero and Pindyck (1996), Caballero (1999), Bertola and Caballero (1994), Bloom et al. (2007), Christiano et al. (2014) and **?**, while Gilchrist et al. (2014) survey the associated literature.

Macroeconomics literature highlights the importance of t different shocks, that include demand and supply side shocks, while it also emphasises the effects of these shocks during the different phases and components of the economic cycle. A case in point is the widely accepted phenomenon that the trend break, as well as the protracted underperformance of South Africa's minerals industry, relative to the total economy, since the 1970s was a problem of structural misalignments, hence the sector cannot be affected by changes in economic stabilisation policies, such as financial, monetary and fiscal policies. According to Blanchard et al. (1986), Shapiro (1987), Blanchard and Quah (1988), Shapiro and Watson (1988), Quah (1988), Kydland and Prescott (1990), Gali (1992) as well as 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. Futhermore, the European Central Bank (ECB) (2012) and Morgan Stanley Capital International (MSCI) (2014) contend that the investment literature distinguishes between the types of industries, such as defensive, cyclical and sensitive industries, based on how they respond to economic fluctuations over the economic cycle.

Conventional macroeconomic models, further, distinguish between alternative "anchors" to stabilise the cyclical behavior of economic activity. The short term, or transitory, economic fluctuations emanate from changes in monetary, financial and fiscal policies as well as consumer and business sentiments. 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. The demand and supply side economic management paradigm, therefore, suggest the decomposition of macroeconomic indicators into their transitory and permanent components. A discussion on the isolation of economic variables into the short and long run components can be found in Kydland and Prescott (1990), King and Rebelo (1993), Romer (1993) and Stock and Watson (1999). Hodrick and Prescott (1997), Baxter and King (1999) as well as Christiano and Fitzgerald (2003), provide methodological details. Since Burns and Mitchell (1946), extraction of the business cycle component is a long tradition in macroeconomics.

This paper analyses the reaction of the minerals industry to market uncertainty *developments* in South Africa. This is achieved by augmenting a Taylor (1993) rule type central bank monetary policy reaction function with the Chicago Board Options Exchange's (CBOE's) Volatility Index (VIX), or Market uncertainty, index. Understanding the reaction of the minerals industry to Market uncertainty *developments* over the economic cycle is important to mining authorities and policymakers alike. This is particularly the case given the trend break, as well as the protracted underperformance of South Africa's minerals industry, relative to the total economy, since the 1970s, as discussed. Diebold and Rudebusch (1970), Kydland and Prescott (1990), Romer (1993) and Kose and Terrones (2015), among others, argue that the different economic sectors respond differently to endogenous and exogenous economic shocks as well as to the long run and short run disturbances. According to the European Central Bank (ECB) (2016), quantifying market uncertainty and its impact on economic activity is, thus, crucial for assessing the current macroeconomic situation and forming a view on its outlook.

The paper is organised as follows. The next section discusses data and this is followed by the specification of the model and the estimation technique. The subsequent section presents 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 Market uncertainty *developments*. The variables comprise output of mining and quarrying, inflation rate, monetary policy interest rate and Market uncertainty index. Mining output is Gross Value Added (GVA) of mining and quarrying, or the minerals industry. Inflation rate, or the change in annual Consumer Price Index (CPI), is the 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. Market uncertainty index is the Chicago Board Options Exchange's (CBOE's) measure of stock market volatility, or uncertainty, based on S&P 500 options, often called the fear index. The data on mining output and inflation rate was sourced from Statistics South Africa, while data on the interest rate and market uncertainty was sourced from the South African Reserve Bank. The descriptions the variables are presented in Table 1. Mining output is denoted $GVAMng$, inflation rate is denoted $CPIRate$, monetary policy interest rate, is denoted $CBRate$, while $VIXAll$ denotes Market uncertainty index.

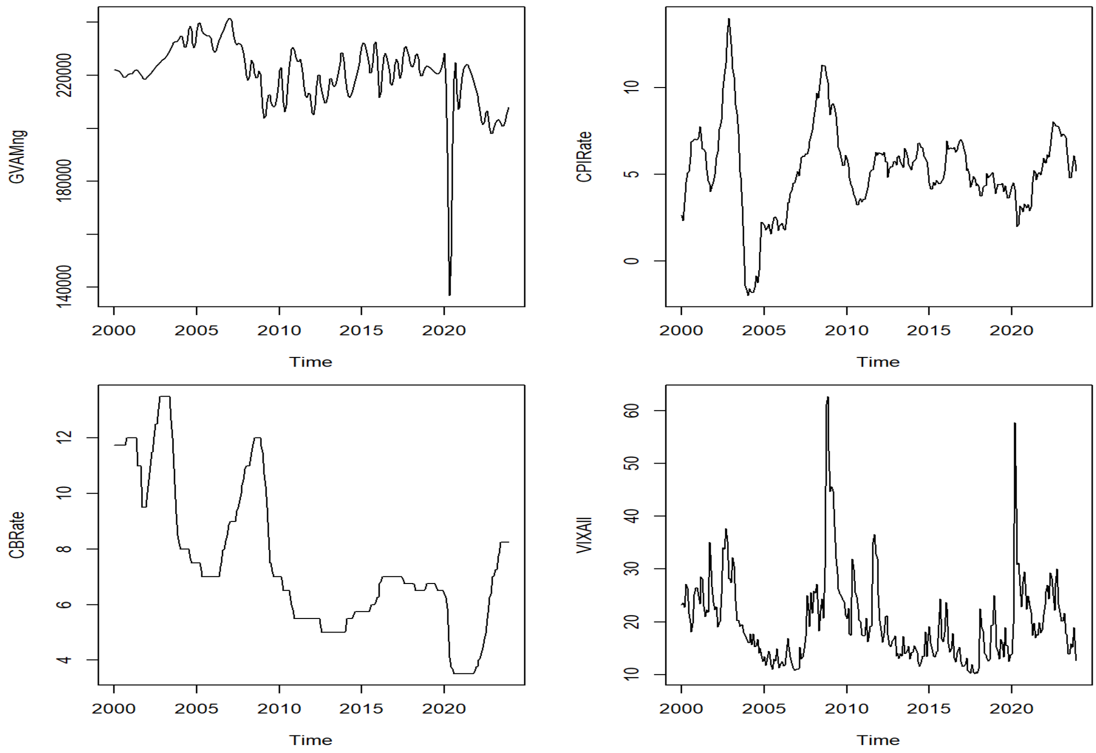
Variable	Denotation	Description
Mining output	GVAMng	Gross Value Added (GVA) of the mining and quarrying, or minerals, industry
Inflation rate	CPIRate	Inflation rate, or annual Consumer Price Index (CPI), is the annual headline consumer price inflation
Interest rate	CBRate	Central bank policy rate and is the rate at which private sector banks borrow from the central bank
Market uncertainty	VIXAll	Chicago Board Options Exchange's (CBOE's) stock market volatility, or uncertainty, index based on S&P 500

Notes: Data sourced from Statistics South Africa and South African Reserve Bank. Output of mining and quarrying is denoted $GVAMng$, consumer price inflation rate, is denoted CPI, central bank monetary policy interest rate, is denoted $CBRate$ and $VIXAll$ denotes Market uncertainty index.

Table 1: Description of the variables

The evolutions 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 before decreasing 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. Movements of the central bank monetary policy interest rate closely mirrored the fluctuations 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 downward trend between 2000 and 2023 with notable spikes and peaks in 2003, 2008 and 2023, 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.

Market uncertainty, or Chicago Board Options Exchange's (CBOE's) Volatility Index (VIX), index display two major epiosodes of high market uncertainty, on average, between 2000 and 2023, or throughout the sample period. The market uncertainty index was somewhat elevated from 2001, peaking in 2003, while it accelerated sharply between 2007 and 2009. The increase in market uncertainty index witnessed in the period leading up to 2003 coincided with the 9/11 attacks and the Iraq war, while the increase in market uncertainty index witnessed in the period leading up to 2008 coincided



Notes: Data sourced from Statistics South Africa and South African Reserve Bank. Output of mining and quarrying is denoted $GVAMng$, consumer price inflation rate, is denoted CPI, central bank monetary policy interest rate, is denoted $CBRate$ and $VIXAll$ denotes Market uncertainty index.

Figure 1: Plots of the variables

with the the Global financial crisis. The Market uncertainty index then remained relatively elevated between 2010 and 2012, coincident with the Sovereign debt crisis, while it subsequently decreased until 2019, albeit a brief increase in 2016, consistent with the Brexit, or the withdrawal of the United Kingdom from the European Union. Another sharp acceleration in the market uncertainty index was realised in 2020, which concides with the onset of the Covid 19 pandeminc, while the Market uncertainty index increased in 2020 consitent with the Russia Ukrainian War. The market uncertainty index was muted between 2004 and 2006, from 2013 to 2015 and from 2018 and 2019 as well as in 2023.

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) 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 Market uncertainty *developments* over the economic cycle.

Methodology

A Vector Autoregression (VAR) model is estimated to capture the relationship between the minerals industry and market uncertainty *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 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 surprise movements, after taking the Vector Autoregression (VAR) model's past values, or lags, into account.

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 the recent contributions include Lütkepohl (2005), Koop and Korobilis (2010) as well as 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 no disadvantageous consequences on the inference of the parameters of the model.

Results

A Bayesian Vector Autoregression (BVAR) model was estimated to capture the relationships between the minerals industry and market uncertainty *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, in contrast to sampling from the 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. A Taylor (1993) rule type central bank monetary policy reaction function with the output of mining and quarrying industry is, thus, augmented with market uncertainty index as follows

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

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, U_t denotes market uncertainty index, while $\bar{U_t}$ denotes its natural rate. θ_π, θ_Y and θ_U 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 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 the monetary policy decisions affect the 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 whenever output equals its steady state level, consumer price inflation equals its target rate and market uncertainty equals its 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 market uncertainty index, denoted $VIXAll_t$. Y_t in Equation 1 can, thus, be rewritten as

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

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 model variables also changes the equations, coefficients as well as 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 to developments in market uncertainty.

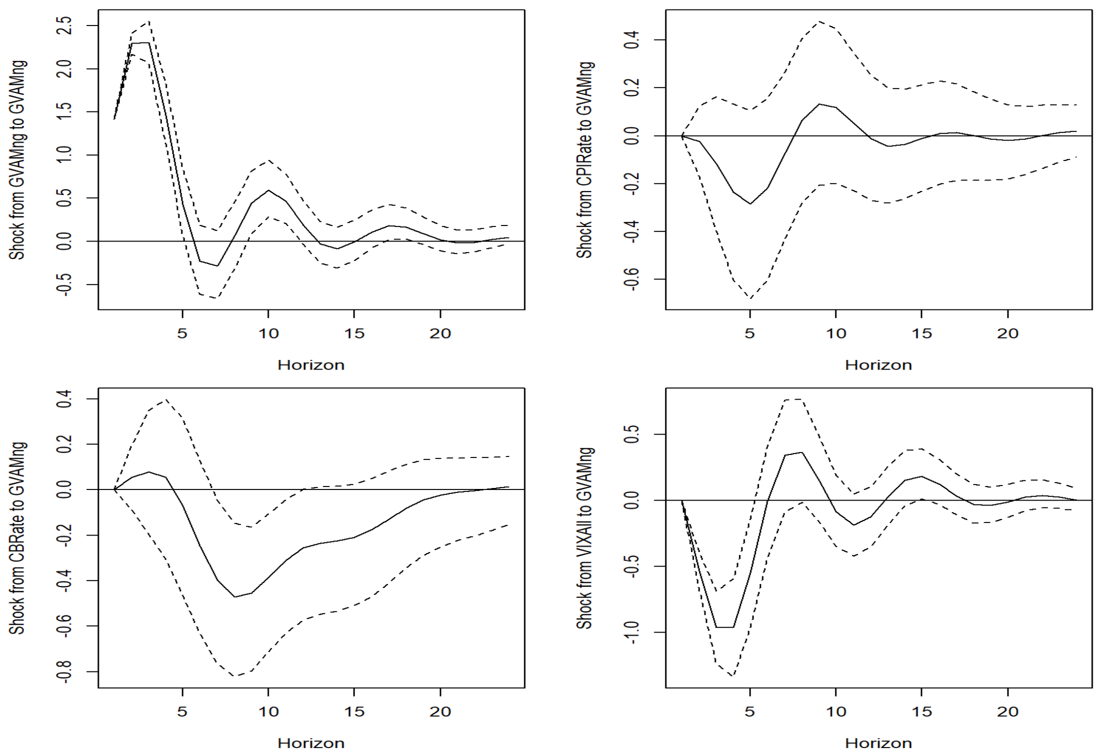
The variables were transformed to stationarity in that they were decomposed into deviations from their long term trends. The detrending is useful conceptually because it eliminates the common steering force that time may have on each variable series and hence induces stationarity. As such, the variables 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.

The Impulse Response Functions (IRFs) of a 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 increases and peaks at 2.30 percentage points after 3 months. The initial increase is followed by a rapid decrease where the minerals industry output bottoms out at -0.28 percentage points after 7 months. The initial increase in in output of the minerals industry remains statistically significant for about 11 months following which its potency begins to progressively wane, or dissipate. Output of the minerals industry, thereafter, fluctuates and rapidly moves towards its steady state level in about 19 months. Following an unexpected 1 percentage point increase in consumer price inflation, output of the minerals industry initially decreases and bottoms out at -0.28 percentage points after 5 months. Output of the minerals industry then increases, peaking at 0.13 percentage points after 9 months. Minerals industry output then fluctuates, and progressively tends, towards its natural rate. The effect of the unexpected, or surprise, increase in consumer price inflation is statistically insignificant during all time periods.

Following an unexpected 1 percentage point increase in monetary policy interest rate, output of the minerals industry increases slightly and peaks after 2 months. The initial increase in output of the minerals industry is followed by a decrease where the minerals industry output bottoms out at -0.48 percentage points after 8 months. The effect of the surprise increase in monetary policy interest rate is, however, statistically significant between 7 and 11 periods, following which it begins to progressively discipate and hence the minerals industry output gradually tends towards its steady state level. Following an unexpected, or surprise, 1 percentage point increase in market uncertainty, output of the minerals industry decreases and bottoms out at -0.96 percentage points after 3 months. The initial decrease is followed by an increase where output of the minerals industry peaks out at 0.37 percentage points after 8 months. The increase in output of the minerals industry is followed a decrease and subsequent fluctuation and gradual movement of output of the minerals industry towards its equilibrium, or steady state, level after 18 months. The effect of an unexpected, or surprise, increase in market uncertainty on output of the minerals industry is statistically significant up to 6 months.

The Impulse Response Functions (IRFs) of a 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, that output of the minerals industry initially increases and peaks at 2.34 percentage points after 3 months and that the effect remains statistically significant for about 12 months. Following an unexpected 1 percentage point increase in output of the minerals industry, consumer price inflation decreases and bottoms out at -0.06 percentage points after 6 months. The initial decrease is followed by a sustained increase where consumer price inflation peaks at 0.02 percentage points after 24 months. Consumer price inflation subsequently decreases and progressively, tends towards and fluctuates around, its equilibrium, or steady state, level. The effect of a surprise increase in output of the mining industry on consumer price inflation is statistically insignificant during all time periods.

Following an unexpected 1 percentage point increase in output of the minerals industry, the central

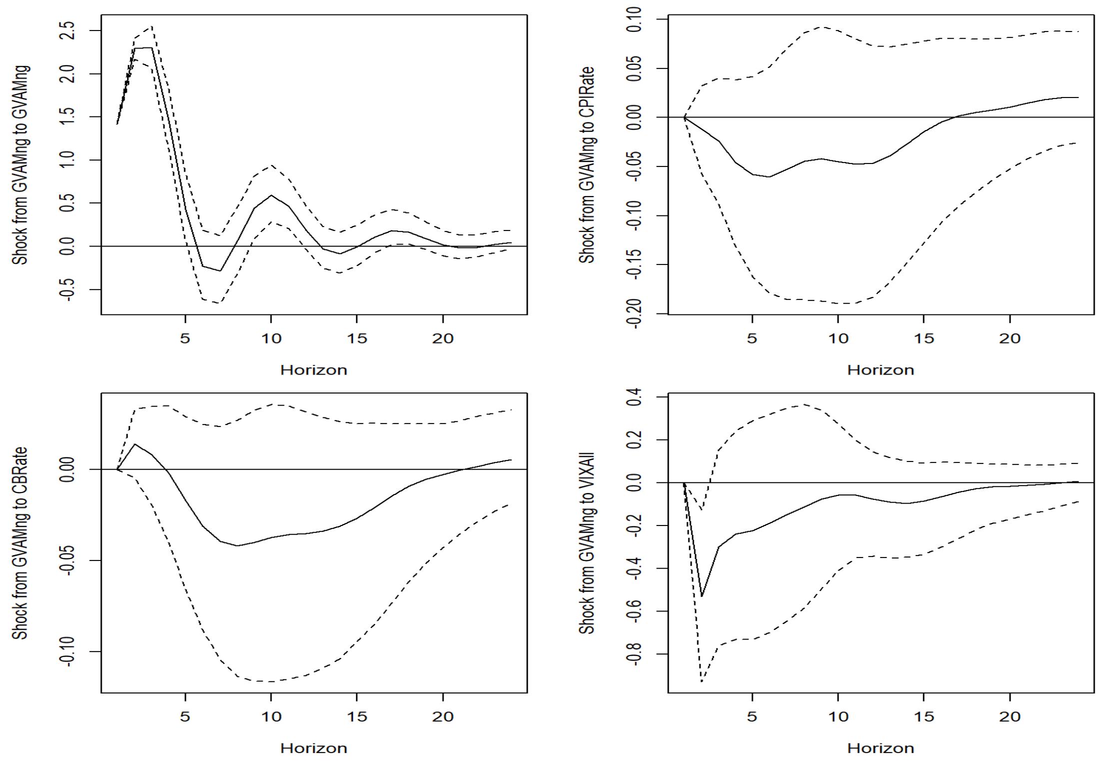


Notes: Data sourced from Statistics South Africa and South African Reserve Bank. Output of mining and quarrying is denoted $GVAMng$, consumer price inflation rate is CPI, central bank monetary policy interest rate is $CBRate$ and $VIXAll$ denotes market uncertainty index. The x axis depicts the horizon of the Impulse Response Functions (IRFs)

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

bank monetary policy interest rate initially increases and peaks at 0.01 percentage points after 2 months. The initial increase is followed by a decrease where central bank monetary policy interest rate bottoms out at -0.04 percentage points after 8 months. The monetary policy interest rate subsequently increases and 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 the central bank monetary policy interest rate is, however, statistically insignificant in all time periods. Following an unexpected 1 percentage point increase in output of the minerals industry, market uncertainty index initially decrease and bottoms out at -0.30 percentage points after 2 months. The initial sharp decrease in market uncertainty index is followed by a sustained increase where market uncertainty index fluctuates and progressively tends towards, its equilibrium, or steady state, level. The effect of the increase in output of mining and quarrying on market uncertainty is statistically significant up to 2 months, which indicates a weak feedback effect between market uncertainty and output of the minerals industry.

Market uncertainty, a phenomenon where economic agents cannot contemplate the possible states of events, or characterise their probability distributions, and their outcomes until further information becomes available, has direct implications for economic activity, affecting business investment and household consumption decisions. The empirical results provide evidence of a statistically significant effect of an unexpected, or surprise, increase in market uncertainty on output of the minerals industry decreases and bottoms out at -0.96 percentage points after 3 months. The results further show that the effect of an unexpected, or surprise, increase in market uncertainty on output of minerals industry is statistically significant up to 6 months. The results are consistent with the the theoretical and empirical prescripts on market uncertainty and the economic cycle. In particular, Gilchrist et al. (2014), Kose and Terrones (2015), Bobasu et al. (2020) as well as Gieseck and Rujin (2020), among others, provide evidence that uncertainty about the economy runs contrary to the business cycle, as discussed. Macroeconomists have, thus, made a compelling argument about the countercyclical behavior of the cross sectional dispersion of economic variables, such as employment, income, business profits, productivity and stock returns and that these variables reflect fluctuations in market uncertainty.



Notes: Data sourced from Statistics South Africa and South African Reserve Bank. Output of mining and quarrying is denoted $GVAMng$, consumer price inflation rate is CPI, central bank monetary policy interest rate is $CBRate$ and $VIXAll$ denotes market uncertainty index. 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

Conclusion

This paper analysed the reaction of the minerals industry to market uncertainty *developments* in South Africa. This was achieved by augmenting a Taylor (1993) rule type central bank monetary policy reaction function with the Chicago Board Options Exchange's (CBOE's) Volatility Index (VIX), or market uncertainty, index. The empirical results have provided evidence of a statistically significant effect of an increase in market uncertainty on output of the minerals industry, which decreases and bottoms out after 3 months, where this effect is statistically significant up to 6 months. The results further shown that following an increase in output of the minerals industry, the market uncertainty index decrease slightly and bottoms out after 2 months, with a statistically significant effect up to 2 months, which indicates a weak feedback effect between market uncertainty and output of the minerals industry. Market uncertainty is, thus, important economic activity, hence policymakers should continue to monitor the developments in market uncertainty to support economic activity as well as the minerals industry. Several indicators, such as inflation, monetary policy interest rates, Government expenditure and taxation, foreign exchange rates and prices of commodities, affect economic activity, at least theoretically, hence it is important for future research to analyse their impact on the minerals industry.

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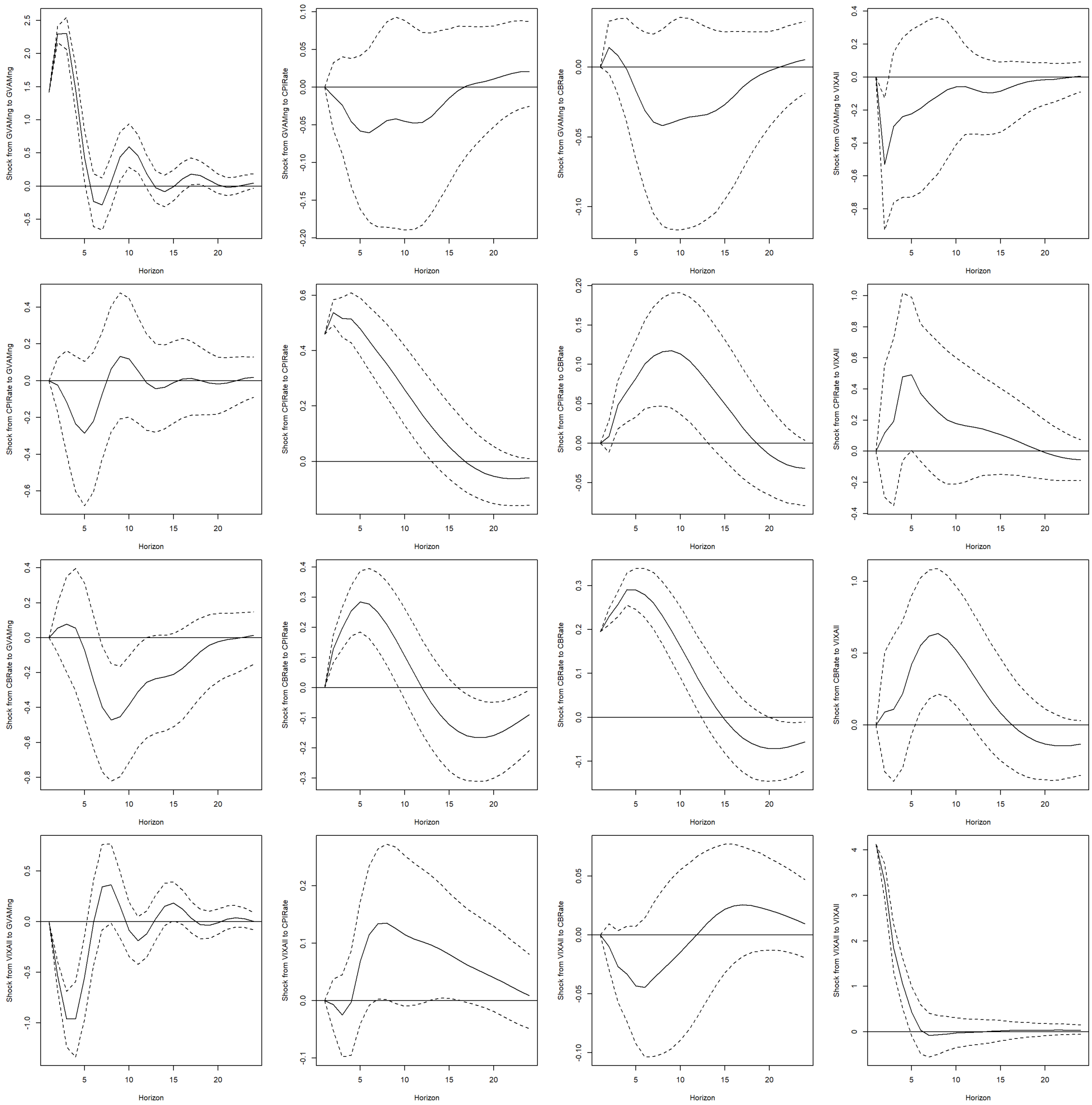
Appendix

Appendix 1. Complete Impulse Response Functions (IRFs)

The complete Impulse Response Functions (IRFs) of a Vector Autoregression (VAR) model with market uncertainty index 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 and South African Reserve Bank. Output of mining and quarrying is denoted $GVAMng$, consumer price inflation rate is CPI, central bank monetary policy interest rate is $CBRate$ and $VIXAll$ denotes market uncertainty index. The x axis depicts the horizon of the Impulse Response Functions (IRFs).

Figure 4: Complete Impulse Response Functions (IRFs) with market uncertainty index