# Geopolitical risk developments and the minerals industry

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## Abstract

This paper analyses the reaction of the minerals industry to geopolitical risk *developments* in South Africa. This is achieved by augmenting a Taylor (1993) rule type central bank monetary policy reaction function with the indicator of geopolitical risk. The results provide evidence of a statistically significant effect of an increase in geopolitical risk on output of the minerals industry, which initially decreases and bottoms out after 5 months, followed by a slight recovery and another decrease, where output of the minerals industry bottoms out again after 13 months, the effect of which is statistically significant between 12 and 14 months. The results further show no statistically significant effect of output of the minerals industry on geopolitical risk implying a unidirectional nexus between these indicators. The results are consistent with the hypothesis that elevated geopolitical risk undermines cross national consumer, business and investor confidence, consequently culminating in depressed economic conditions. Geopolitical risk is important for economic activity, hence policymakers should monitor developments in geopolitical conditions to support economic growth as well as the minerals industry.

**JEL Classification**:C10, E30, F20, L72
**Keywords**: Geopolitical risk, Minerals industry, Economic cycles

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# Introduction

Geopolitical risk, which reflects potential instability and disruption emanating from tensions in international relations that encompass diplomatic conflicts, which culminate in sanctions and wars that impact cross national consumers, businesses and global stability, has occupied center stage in economics discourse on apparent hegemony by the perceived strong and powerful nations. According to Aiyar and Ilyina (2023) and Caldara et al. (2024a), recent geopolitical events have been a significant driver of global economic and financial market uncertainty. Following decades of increasing global economic integration, the world is facing the risk of geoeconomic fragmentation. Aiyar et al. (2023a) and Attinasi and Mancini (2025), in particular, contend that geopolitical rivalries have fuelled protectionism and cross border restrictions, often justified on national security grounds, as nations seek to safeguard their interests and capabilities. A number of geopolitical hotspots, the most notable which include South China Sea, the Middle East and Eastern Europe, have emerged around the world. According to Alfaro (2023), the escalating geopolitical tensions can adversely affect economic fundamentals, decimating business ventures, resulting in severe losses and even a complete shutdown of business operations.

COVID-19 pandemic and Russia's invasion of Ukraine, among others, have further tested international relations and increased skepticism about the benefits of globalisation, according to Aiyar et al. (2023b), a trend observed after the recent global financial crisis, reversing a multi decade economic integration dating to the middle of the 20th century. A detailed discussion on geopolitical risk and geoeconomic fragmentation, defined as a policy driven reversal of global economic integration, can be found in Caldara and Iacoviello (2022), citeAiyarOthers2023a, Aiyar and Ilyina (2023), Aiyar et al. (2023a) as well as Caldara et al. (2024b). Original literature on the benefits of economic globalisation, in particular, the liberalisarion, or free flow, of goods and services, production factors, financial flows and technology etc. can be found in Dornbusch (1992), Obstfeld (1994), Eichengreen and Irwin (1995) as well as Frankel and Romer (1999), while Acemoglu et al. (2015), Bloom et al. (2016) and Bloom et al. (2018) discuss trade restrictions and spread of technological advancements. The consequences of geopolitical risk and geoeconomic fragmentation, according to Aiyar et al. (2023a), countries and companies are increasingly focusing on the resilience of their supply chains, with increasing mention of strategies, such as "re shoring," "near shoring" and "on shoring", in corporate earnings reports.

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 indicators, such as consumer and geopolitical risk, technological advancement, privatisation and deregulation, 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 to 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 geopolitical risk, 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 geopolitical risk *developments* in South Africa. This is achieved by augmenting a Taylor (1993) rule type central bank monetary policy reaction function with the indicator of geopolitical risk. Understanding the reaction of the minerals industry to geopolitical risk *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. A case in point is 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 some economic policies and events. 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.

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 geopolitical risk *developments*. The variables comprise output of mining and quarrying, inflation rate, monetary policy interest rate and geopolitical risk. Mining and quarrying output is Gross Value Added (GVA) of the mining and quarrying, or the minerals industry. Inflation rate, or annual change in Consumer Price Index (CPI), is the annual headline consumer price inflation. Monetary policy interest rate, or central bank interest rate, is the short term interest rate, also called repurchase rate, and is the rate at which private sector banks borrow from the central bank. Geopolitical risk is the potential instability and disruption emanating from a nation's involvement in international affairs. 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 geopolitical risk index was sourced from matteoiacoviello.com, which is an index constructed by Caldara and Iacoviello (2022). The descriptions and sources of the variables are presented in Table 1. Output of Mining and quarrying is denoted $GVAMng$, inflation rate, is denoted $CPIRate$, central bank monetary policy interest rate, is denoted $CBRate$, while $GPRIdx$ denotes geopolitical risk.

| 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 |
| Geopolitical risk | GPRIdx | Economic, political and social instability and disruption due to a nation's involvement in international affairs |

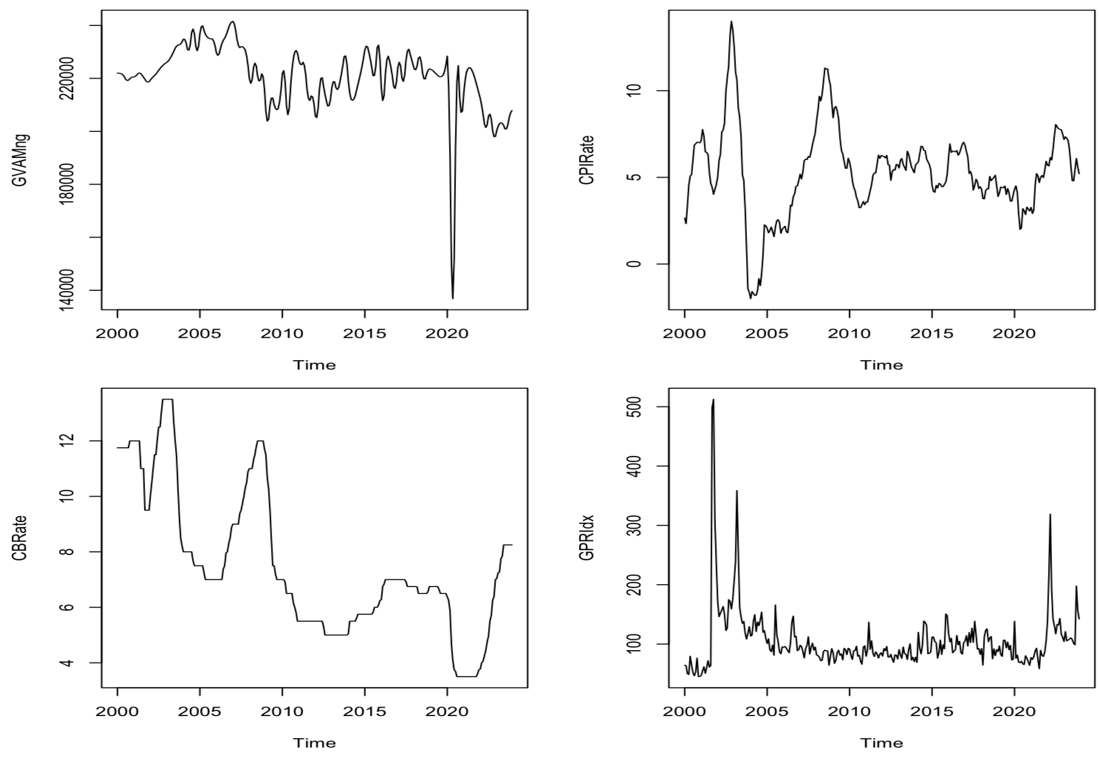
Notes: Data sourced from Statistics South Africa, South African Reserve Bank and the World Bank. Mining and quarrying output is denoted $GVAMng$, consumer price inflation rate, is denoted $CPI$, central bank monetary policy interest rate, is denoted $CBRate$ and $GPRIdx$ denotes geopolitical risk.

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.

Geopolitical risk was low and stable between 2000 and late 2001. The indicator accelerated significantly, peaking in late 2001, decreased and bottomed out around mid 2002. The elevated geopolitical risk in 2001 coincided with the 9/11 terrorist attack on the World Trade Center and Pentagon in the United States. Geopolitical risk increased from mid 2002 and spiked again and peaked in early 2003, coincident with U.S. invasion of Iraq on accusations about weapons of mass destruction. Geopolitical risk subsequently decreased and bottomed out mid 2005, where it remained low and somewhat range bound between from mid 2005 and early 2014, while increased again in early 2014 and remained somewhat elevated and volatile until early 2020. The elevation in geopolitical risk in this period coincided with the tensions on the Russian annexation of the Crimea peninsula and the Russia-Ukraine crisis, the Paris terrorist attacks, UK's departure from the European Union or Brexit, and rapid expansion of ISIS as well as the rise in tensions between China and Japan over territorial disputes. Geopolitical risk decreased slightly between early 2020 and mid 2021, where it spiked and peaked in early 2022, while it decreased and bottomed out in mid 2023, where it accelerated again peaked in late 2023, where volatility in this period was due to Russia invasion of Unkraine and renewed Middle East tensions.

The variables were transformed to the deviation from their Hodrick and Prescott (1997) trends. 24




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 $GPRIdx$ denotes geopolitical risk. The x axis depicts the time period.

Figure 1: Plots of the variables

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 *developments* in geopolitical risk over the economic cycle.

# Methodology

A Vector Autoregression (VAR) model is estimated to capture the relationship between the minerals industry and the developments in geopolitical risk. Examination of the Impulse Response Functions (IRFs) from a Vector Autoregression (VAR) model are analysed understand the reaction of the minerals industry and geopolitical risk. 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 $\Sigma$ 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, $\theta_i$ 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 geopolitical risk, 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). A 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 an alternative to drawing samples 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 consumer, business and investor sentiments. A Taylor (1993) rule type central bank monetary policy reaction function with the output of mining and quarrying industry is, thus, augmented with geopolitical risk as follows

$$i_t = \rho + \theta_\pi(\pi_t - \pi_t^*) + \theta_Y(Y_t - \bar{Y}_t) + \theta_G(G_t - \bar{G}_t) + \epsilon_t \tag{5}$$

where $i_t$ is the nominal interest rate, $\rho$ is the natural rate of interest, $\pi_t$ is the inflation rate, $\pi_t^*$ is the central bank target for inflation, $Y_t$ is output, $\bar{Y}_t$ is the natural rate of output, $G_t$ denotes geopolitical risk, while $\bar{G}_t$ is the natural rate of geopolitical risk. $\theta_\pi$, $\theta_Y$ and $\theta_G$ 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 geopolitical risk from its natural rate, respectively. $\epsilon_t$ is the error, or disturbance, 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 condition, in that when output equals its steady state level, inflation is the same as its target rate and geopolitical risk 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 geopolitical risk, denoted $GPRIdx_t$. $Y_t$ in Equation 1 can, therefore, be rewritten as

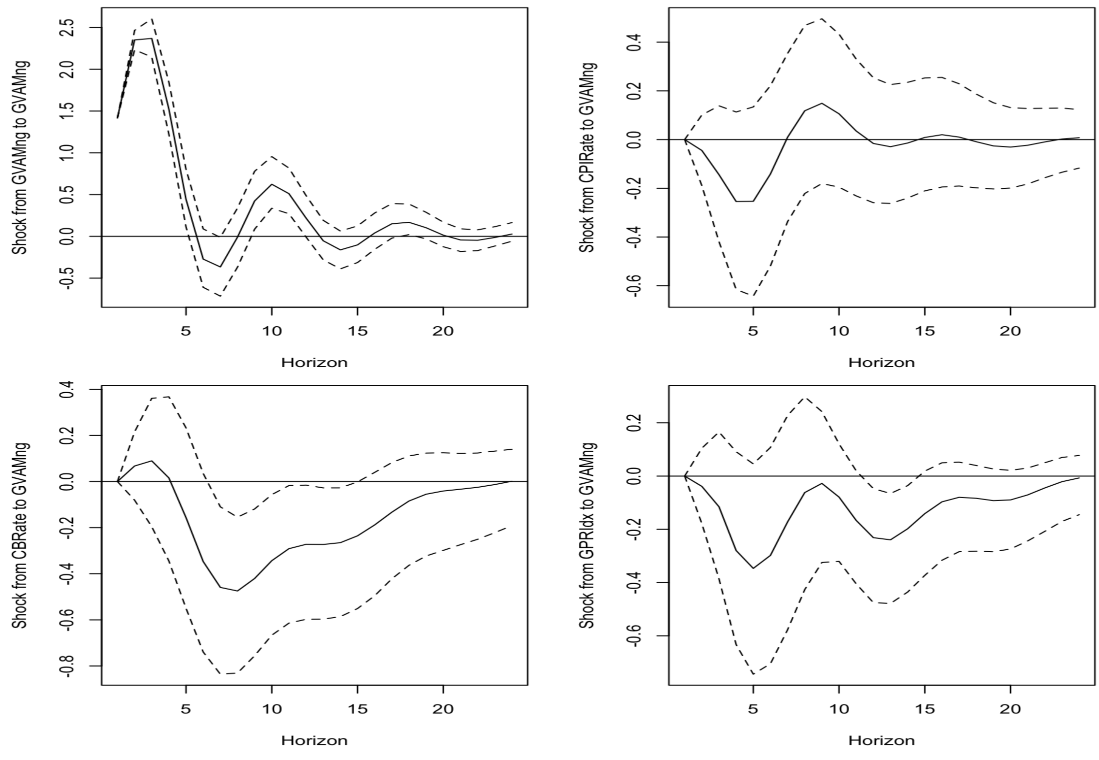
$$Y_t = (GVAMng_t, CPI_t, CBRate_t, GPRIdx_t) \tag{6}$$

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 changes the equations, coefficients and the 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 all other variables 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 aim is to analyse the reaction of the minerals industry output to the developments in geopolitical risk.

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 2.36 percentage points after 3 months. The increase is followed by a rapid decrease where the minerals industry output bottoms out at -0.37 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 -0.25 percentage points after 5 months. Output of the minerals industry then increases, peaking at 0.15 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, nevertheless, 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 $GPRIdx$ denotes geopolitical risk. The x axis depicts the horizon of the Impulse Response Functions (IRFs).

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

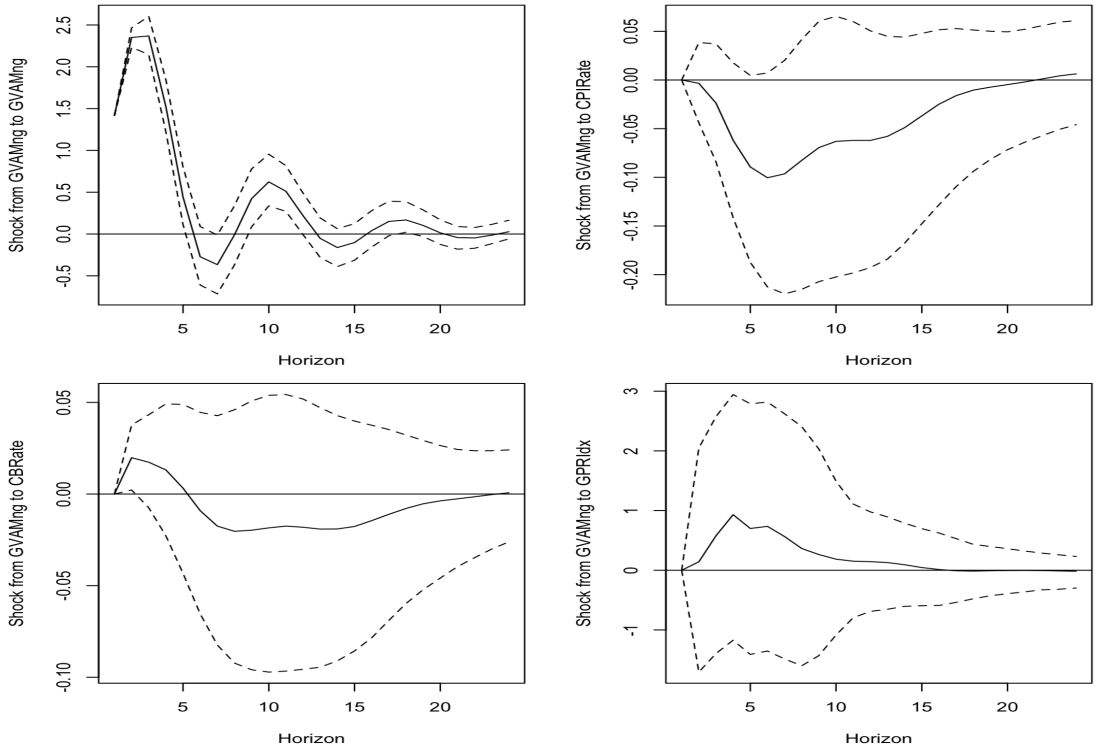
Following an unexpected, or surprise, 1 percentage point increase in monetary policy interest rate, output of the minerals industry increases slightly and peaks at 0.09 percentage points after 2 months. The initial increase in output of the minerals industry is followed by a decrease, where the minerals 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, only statistically significant between 7 and 15 periods, following which such effect begins to progressively dissipate and hence the minerals industry output gradually tends towards its steady state level. Following an unexpected, or surprise, 1 percentage point increase in geopolitical risk, output of the minerals industry initially decreases and bottoms out at -0.35 percentage points after 5 months. The initial decrease is followed by a slight recovery followed by another decrease, where output of the minerals industry bottomed out at -0.24 percentage points after 13 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 23 months. The effect of the unexpected, or surprise, increase in geopolitical risk on output of mining and quarrying is only statistically significant between 12 and 14 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, where output of the minerals industry initially increases and peaks at 2.36 percentage points after 3 months. The increase is followed by a rapid decrease where the minerals industry output bottoms out at -0.37 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 output of the minerals industry, consumer price inflation decreases and bottoms out at -0.10 percentage points after 6 months. Consumer price inflation subsequently increases progressively, tends towards and fluctuates around, its equilibrium level in about 21 months. The effect of the surprise increase in minerals industry output on consumer price inflation is statistically insignificant in all time periods.

Following an unexpected, or surprise, 1 percentage point increase in output of the minerals industry, the central bank monetary policy interest rate initially increases and peaks at 0.02 percentage points after 2 months. Central bank monetary policy interest rate subsequently decreases steadily and bottoms out at -0.02 percentage points after 8 months. Central bank monetary policy interest rate remains depressed but subsequently increases progressively, tends towards and fluctuates around, its equilibrium, or steady state, level after 22 months. The effect of the surprise increase in output of the minerals industry on consumer price inflation is, however, statistically insignificant in all time periods. Following an unexpected, or surprise, 1 percentage point increase in output of the minerals industry, geopolitical risk initially increase and peaks out at 0.91 percentage points after 4 months. Geopolitical risk then decreases progressively, tends towards and fluctuates around, its equilibrium, or steady state, level after 17 months. The effect of the surprise increase in output of the minerals industry on the indicator of geopolitical risk is, however, only statistically insignificant in all time periods, which implies a unidirectional effect between the geopolitical risk indicator and minerals industry output.

Geopolitical risk, or instability and disruption from a nation's involvement in international affairs, has had important implications for macroeconomics fluctuations around the world, according to Aiyar et al. (2023a) and Alfaro (2023), fuelling a rise in conflicts, protectionism and cross border restrictions, among others, with adverse consequences on economic fundamentals, decimating cross national consumer, business and investor sentiments. Visual inspection of the index of geopolitical risk shows two episodes of elevated instability and disruption, in particular, between late 2001 and mid 2005, coincident with 9/11 terrorist attack the U.S. invasion of Iraq, as well as between mid 2021 and late 2023, coincident with due to Russia invasion of Unkraine and renewed Middle East tensions. The index of geopolitical risk was, nevertheless, relatively muted between mid 2005 and towards the end of 2023, albeit volatile, indicating no significant geopolitically risky events, that adversely impacted on cross national consumers, businesses and global stability, in this time period. The recent episodes of elevated geopolitical risk, justified on national security grounds as nations seek to safeguard their interests and capabilities, have tested international relations and increased skepticism about the benefits of globalisation, according to Aiyar et al. (2023b), reversing a multiple decade economic integration.

The results provide evidence of a somewhat statistically significant effect of an increase in geopolitical risk on output of the minerals industry, which initially decreases and bottoms out at -0.35




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 $GPRIdx$ denotes geopolitical risk. 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

percentage points after 5 months, followed by a slight recovery as well as another decrease, where output of the minerals industry bottomed out at -0.24 percentage points after 13 months. The effect of the unexpected, or surprise, increase in geopolitical risk on output of mining and quarrying is only statistically significant between 12 and 14 months. The results are consistent with the hypothesis that an increase in geopolitical risk, which emanating from tensions in international relations, undermines the confidence of cross national consumers, businesses and global stability, as discussed in Aiyar and Ilyina (2023) and Caldara et al. (2024a). However, such an effect of elevated geopolitical risk seems minimal in the case of South Africa, only briefly taking effect between 12 and 14 months ex post, even though output of the minerals industry remains in a depressed state up to 23 months since an onset of geopolitically risky events. As discussed, there was only two episodes of elevated geopolitical risk during the sample period, between late 2001 and mid 2005 as well as between mid 2021 and late 2023, which could underestimate the adverse effect of geopolitical events on output of minerals industry.

# Conclusion

This paper analysed the reaction of the minerals industry to geopolitical risk *developments* in South Africa. This was achieved by augmenting a Taylor (1993) rule type central bank monetary policy reaction function with the indicator of geopolitical risk. The results provide evidence of a statistically significant effect of an increase in the indicator of geopolitical risk on output of the minerals industry, which initially decreases and bottoms out at -0.35 percentage points after 5 months, followed by a slight recovery and another decrease, where output of the minerals industry bottoms out at -0.24 percentage points after 13 months. The effect of the unexpected increase in geopolitical risk on output of mining and quarrying is only statistically significant between 12 and 14 months. The results are consistent with the hypothesis that elevated geopolitical risk undermines cross national consumer, business and investor confidence, consequently culminating in depressed economic conditions. Geopolitical risk is important for economic activity, hence policymakers should monitor the developments in geopolitical events to support economic growth and the minerals industry. Several economic indicators, such as the monetary policy interest rates, Government expenditure and taxation, foreign investment, prices of commodities and 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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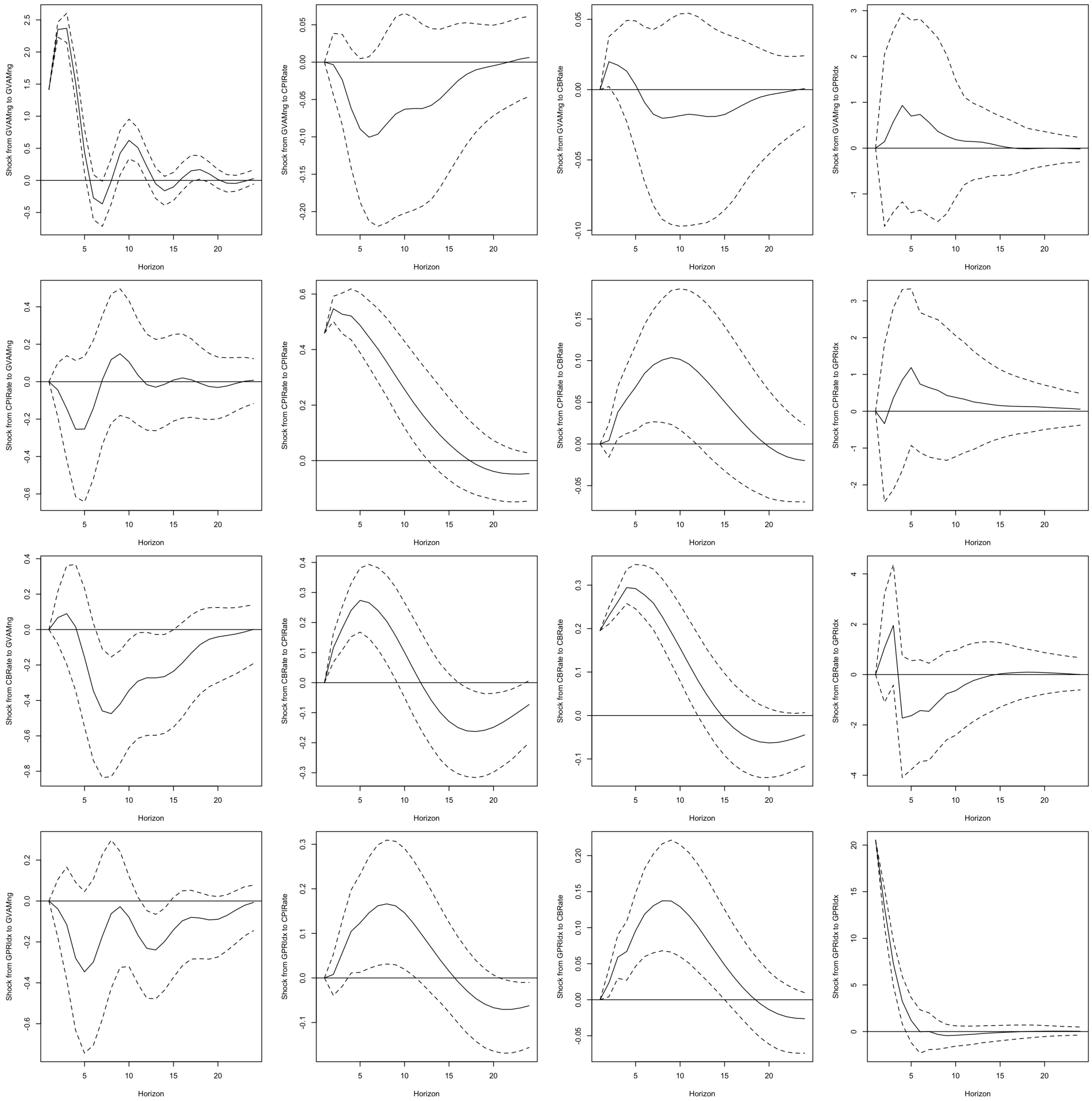
# Appendix

## Appendix 1. Complete Impulse Response Functions (IRFs)

The complete Impulse Response Functions (IRFs) of the Vector Autoregression (VAR) model with geopolitical risk 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 $GPRIdx$ denotes geopolitical risk. The x axis depicts the horizon of the Impulse Response Functions (IRFs).

Figure 4: Complete Impulse Response Functions (IRFs) with geopolitical risk