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Structural minerals fluctuations and the macroeconomy

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Abstract

This paper analyses the *structural* relationship between minerals fluctuations and the macroeconomy in South Africa. This is achieved by isolating the trend component of output of the aggregate minerals industry, together with output of disaggregated minerals and comparing their fluctuations with the trend component of aggregate, or economy wide, output. The results have shown a statistically significant, and predominantly positive, relationship between aggregate, or economy wide, output and output of Mining, at structural, or long term, periodicities. The results have further shown a positive, or procyclical, relationship between aggregate, or economy wide, output and output of Chromium, Manganese and Quarrying, an acyclical relationship between aggregate output and output of Nickel and Other metals, while they show a negative, or countercyclical, relationship between aggregate output and output of Coal, Iron ore, Copper, PGMs, Gold, Diamonds and Other non metals. The paper recommends a comprehensive determination of the temporal relationship between the minerals industry and macroeconomic indicators to inform targeted policy decision making, where appropriate.

JEL Classification: C11, D20, E30, L70
Keywords: Minerals fluctuations, Minerals industry, Economic cycles

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Introduction

Structural economic fluctuations refer to long term shifts in productive capacity of the economy, distinct from short term business cycle fluctuations. According to Ostry et al. (2009), Campbell and Mankiw (1987b), Shapiro and Watson (1988) and Campos et al. (2025), These fluctuations are driven by changes in the fundamental structure of the economy, such as changes in government policy, shifts in consumer preferences, technological advancements, shifts in demographics, changes in resource availability and globalisation. Structural economic fluctuations are associated with supply side economics, which emphasises increasing production, or supply of goods and services, as the primary driver of consumption and economic growth. According to Campos et al. (2025), Neoclassical economics, also known as supply side theory, emphasises the role of supply and demand, or the market mechanism, in determining the production, consumption and valuation of goods and services, achieved by lowering barriers to production in support of economic growth. Neoclassical economics advocates efficient resource allocation and innovation, through promotion of free markets and minimal government intervention, in production of goods and services, according to Ostry et al. (2009).

Economic sectors respond differently to the economic shocks, according to Diebold and Rudebusch (1970) and Romer (1993). The common movement in fluctuations between different industries could be because they are partially driven by common shocks, or the economic events that affect multiple sectors simultaneously, due to the factors that include economic policies, investment and consumption decisions, as discussed. Detailed discussion on macroeconomic shocks can be found in (Nelson and Plosser, 1982), Kydland and Prescott (1990), Nelson (2005) and Christiano et al. (2005), while Diebold and Rudebusch (1970), Blanchard et al. (1986), Campbell and Mankiw (1987a) and Campbell and Mankiw (1987b) discuss the interaction of macroeconomic policies and the economic fluctuations.

Investment literature distinguishes between different types of industries, categorised into cyclical, defensive and sensitive industries, based on how they respond to economic fluctuations, according to European Central Bank (ECB) (2012) and Morgan Stanley Capital International (MSCI) (2014). Corden (1980), Petersen and Strongin (1996) and Beber et al. (2011) argue that companies in cyclical industries are pro, or counter, cyclical, those in defensive industries are acyclical, while sensitive industries respond to economic shocks so that they fall between defensive and cyclical industries.

Conventional macroeconomic models distinguish between alternative "anchors" to stabilise the cyclical behaviour of economic activity. Macroeconomics literature further highlights the importance of the different shocks, that include the demand side and supply side shocks, according to Blanchard et al. (1986), Blanchard and Quah (1988), Quah (1988), Kydland and Prescott (1990), Gali (1992) and Romer (1993). A widely accepted phenomenon is that the trend break, as well as the protracted underperformance, of the minerals industry relative to total economy since the 1970s was a problem of structural misalignments. 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. Paradoxically, South Africa is known for its abundance of mineral resources and is estimated to have the world's fifth largest mining sector, while its companies are major players in the global industry, according to government Communication and Information System (GCIS). The industry could, thus, be perceived not to be affected by the fluctuations in economic indicators, such as monetary, financial and fiscal policies and other factors that include foreign flow goods and services, financial assets and geopolitical events.

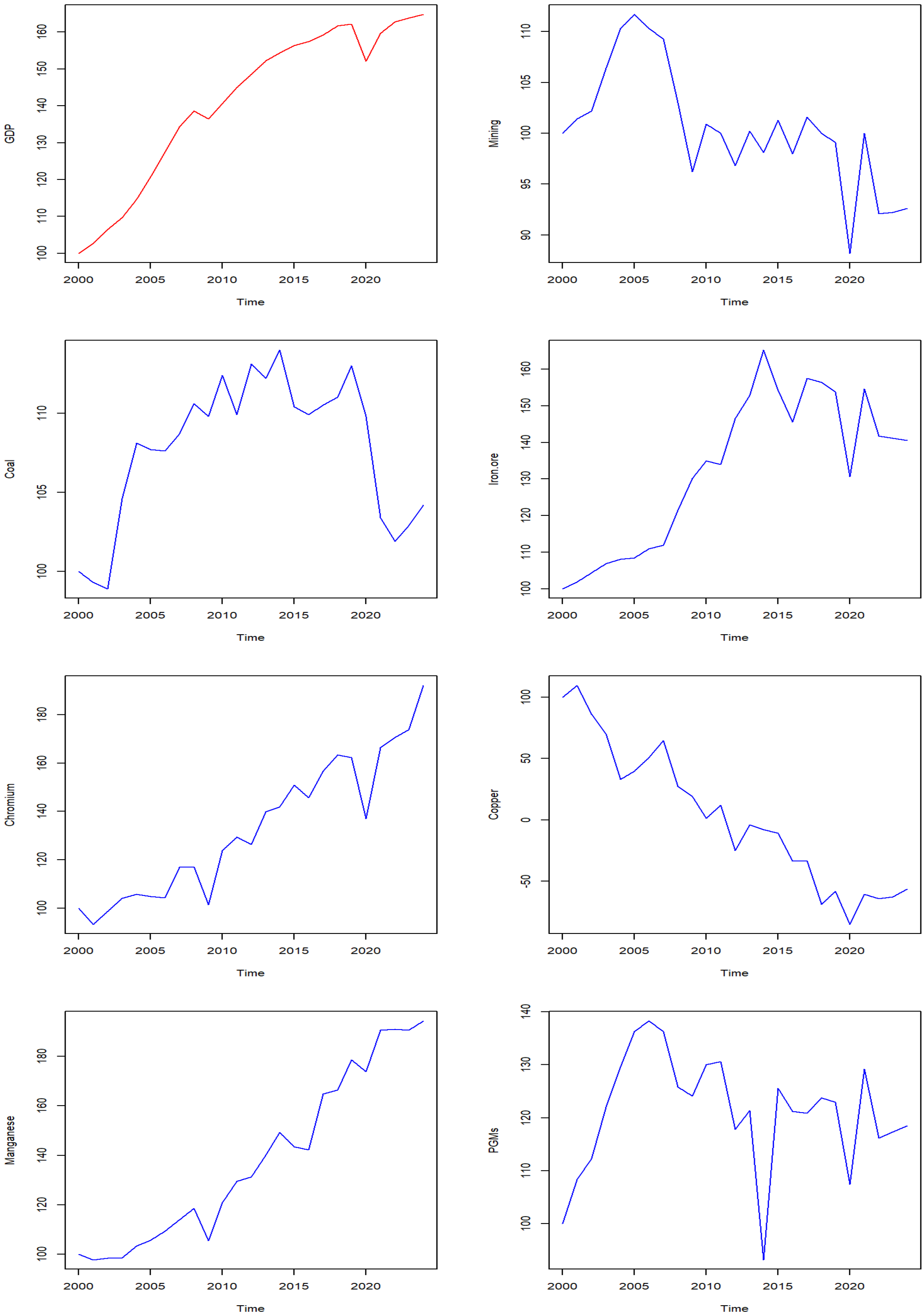
This paper analyses the *structural* relationship between minerals fluctuations and the macroeconomy in South Africa. This is achieved by isolating the trend component of output of the aggregate minerals industry, together with output of disaggregated minerals and comparing their fluctuations with the trend component of aggregate, or economy wide, output. The observed trend break, as well as the protracted underperformance, of the minerals industry relative to the total economy since the 1970s could be a problem of transitory and structural misalignments in fluctuations output of the aggregate minerals industry and output of disaggregated minerals relative to fluctuations of aggregate, or economy wide, output, as discussed. For instance, the common movement or divergence in the fluctuations of disaggregated minerals, as with the aggregate minerals industry, could be because of their difference in behaviour to common endogenous and exogenous economic shocks. Understanding the relationship between minerals fluctuations and the economy is important to mining authorities and policymakers alike. Sound policy formulation necessitates understanding how the aggregate minerals sector and disaggregated minerals behave to common shocks and their transmission mechanisms.

The paper is organised as follows. The next section presents the data, followed by the outline of the methodology and the discussion of the results. Last is the conclusion with recommendations.

Data

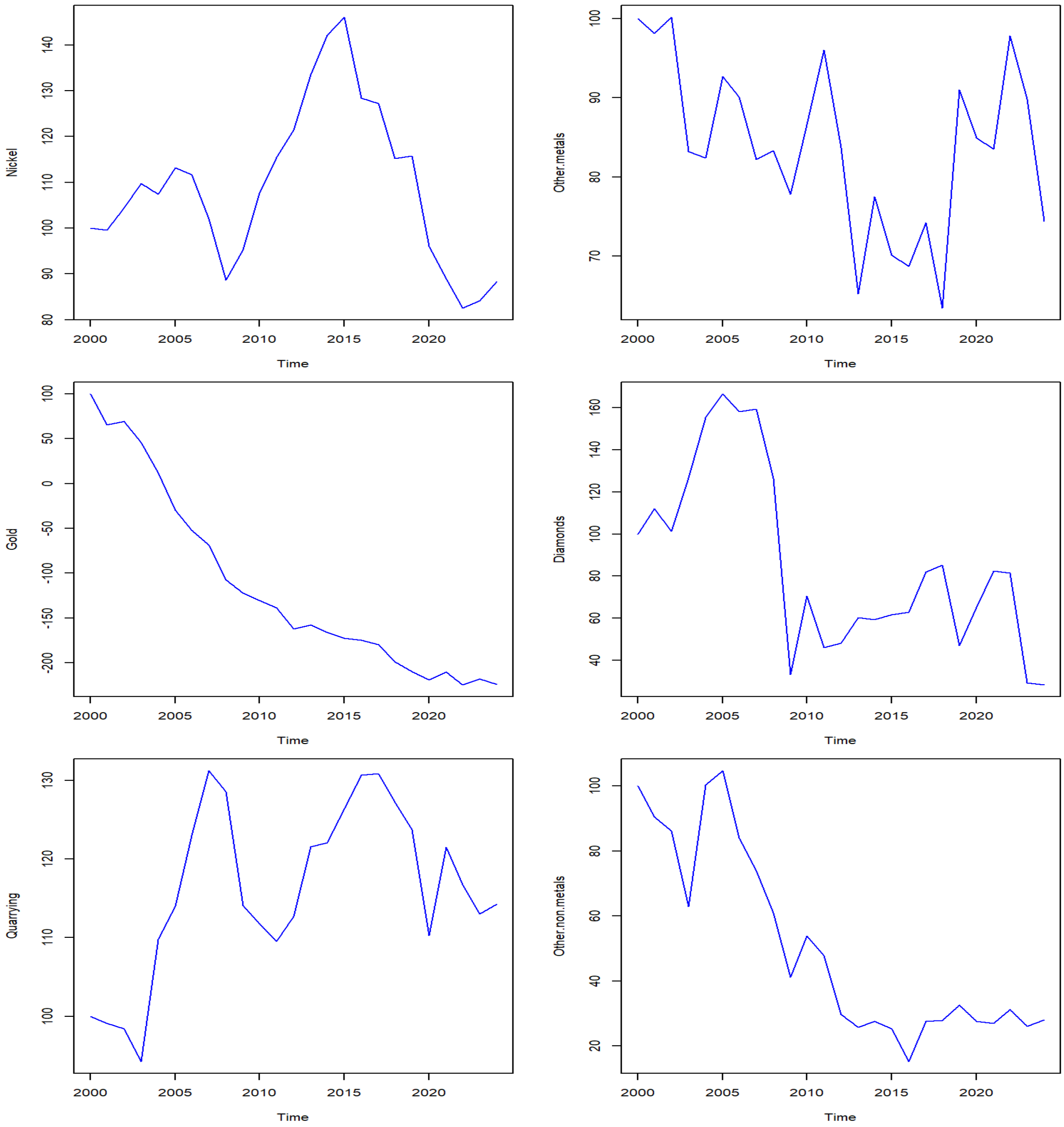
Data from Statistics South Africa spanning the period 2000 to 2024 is used to analyse the relationship between *structural* minerals fluctuations and the macroeconomy. The data comprises the indexes of aggregate, or economy wide, output, as well as aggregate output of the minerals industry, together with disaggregated output of about 12 minerals, where the index values are fixed at 100 in 2000. The disaggregated minerals comprise Coal, Iron ore, Chromium, Copper, Manganese ore, PGMs, Nickel, Other metallic minerals, Gold, Diamonds, Building materials and Other non metallic minerals. The descriptions of the variables are in Table 4 in the Appendix. Platinum Group Metals (PGMs) refer to a group of six chemically similar, precious metals comprising platinum, palladium, rhodium, ruthenium, iridium and osmium. Building materials, or Quarrying, includes building and monumental stone, including ceramic, refractory and other clay, sand and gravel. Other metallic minerals and Other non metallic minerals are metal and non metal related minerals, not elsewhere classified, respectively. The data is consistent with the Standard Industrial Classification (SIC) of all economic activities.

The plots of aggregate, or economy wide, output, as well as aggregate output of the minerals industry, together with the disaggregated output of the minerals are depicted in Figure 1 and continued in Figure 2. Aggregate, or economy wide, output increased, on average, by a cumulative 64.8 percentage points between 2000 and 2024. The trend break in the indicator was realised in 2008 and 2020, consistent with the onset of the global financial crisis and the COVID 19 pandemic. Aggregate output of the Mining industry decreased, on average, by a cumulative 7.4 percentage points between



Notes: Own calculations with data from Statistics South Africa. The data comprises the indexes of output of the minerals industry, together with output of disaggregated minerals as well as aggregate, or economy wide, output.

Figure 1: Variables plots



Notes: Own calculations with data from Statistics South Africa. The data comprises the indexes of output of the minerals industry, together with output of disaggregated minerals as well as aggregate, or economy wide, output.

Figure 2: Variables plots (continued)

2000 and 2024. The indicator peaked in 2005, decreased and remained range bound between 2009 and 2019, while it bottomed out in 2020 and recovered to 2024. Coal increased by a cumulative 4.2 percentage points between 2000 and 2024. The indicator increased between 2000 and 2019 followed by a decrease to 2024. Iron ore increased by a cumulative 40.6 percentage points between 2000 and 2024. The indicator peaked in 2014 followed by a decrease to 2024. Chromium increased by a cumulative 92.1 percentage points between 2000 and 2024, where the trend break in output in the indicator was realised in 2008 and 2020. Copper decreased by a cumulative 156.4 percentage points between 2000 and 2024, where the indicator generally decreased with a temporary recovery in 2006 and 2021.

Manganese increased by a cumulative 94.4 percentage points between 2000 and 2024, with temporary decline in 2009 and 2014. PGMs increased, on average, by a cumulative 18.5 percentage points between 2000 and 2024, where it peaked in 2006 and bottomed out in 2014 and 2020. Nickel decreased by a cumulative -11.7 percentage points between 2000 and 2024, bottomed out in 2008 and 2022, while it peaked in 2015. Other metals decreased, on average, by a cumulative 25.6 percentage points between 2000 and 2024. The indicator was volatile, bottomed between 2013 and 2018 and recovered in 2011 and 2022. Gold decreased by a cumulative -324.0 percentage points between 2000 and 2024, where it decreased consistently throughout the sample period. Diamonds decreased by a cumulative 71.8 percentage points between 2000 and 2024, where it increased notably between 2000 and 2005 following which it decreased and remained subdued until the end of the sample period. Quarrying increased, on average, by a cumulative 14.3 percentage points between 2000 and 2024, where it increased significantly between 2003 and 2007, while it remained volatile to the end of the sample period. Other non metals increased by a cumulative 72.0 percentage points between 2000 and 2024, was volatile between 2000 and 2005, decreased significantly before bottoming out in 2016.

The descriptive statistics of the index values of aggregate, or economy wide, output, as well as aggregate output of the minerals industry, together with the disaggregated output of the minerals are presented in Table 1. The correlation coefficient, which measures the strength and direction of the linear association between two variables, show a strong positive relationship between the indexes of economy wide output and output of Iron ore, Chromium, Manganese and Quarrying. The correlation coefficient also show a strong negative relationship between the indexes of economy wide output and and output of Mining, Copper, Other metals, Gold, Diamonds, Quarrying and Other non metals. The correlation coefficient further show a weak relationship between the indexes of aggregate, or economy wide, output and output of Coal, PGMs and Nickel. The strongest correlations are those between the indexes of aggregate output and output of Iron ore, Chromium, Copper and Manganese, regardless of the direction of causality, while the weakest correlations are those between indexes of aggregate, or economy wide, output and output of PGMs and Nickel. This implies that, at the index level, aggregate, or economy wide, output has a higher linear association with output of Iron ore, Chromium, Copper and Manganese, whilst the opposite is true for output of PGMs and Nickel.

	Cor	Max	Min	Mean	Std Dev
GDP	1.000000	164.829900	100.000000	141.272800	21.228051
Mining	-0.577614	111.700000	88.200000	100.476000	5.9234900
Coal	0.482924	114.000000	98.900000	107.756000	4.5534860
Iron.ore	0.907104	165.300000	100.000000	132.556000	20.760320
Chromium	0.903293	192.100000	93.400000	133.076000	28.362332
Copper	-0.926735	109.600000	-84.900000	1.79600000	57.062418
Manganese	0.880820	194.400000	97.800000	138.332000	34.072089
PGMs	0.050931	138.300000	93.200000	121.160000	10.871714
Nickel	0.126303	146.100000	82.500000	108.980000	17.375749
Other.metals	-0.528557	100.200000	63.400000	83.8720000	10.676396
Gold	-0.986601	100.000000	-224.60000	-114.916000	103.41350
Diamonds	-0.646000	166.700000	28.200000	85.9360000	42.560955
Quarrying	0.675482	131.300000	94.200000	116.208000	10.729318
Other.non.metals	-0.906734	104.800000	15.100000	50.2960000	28.979799

Notes: Own calculations with data from Statistics South Africa. Cor is the correlation coefficient, Max is the maximum observation, Min is the minimum observation, Mean measures the average value, and Std Dev is the standard deviation.

Table 1: Descriptive statistics

The descriptive statistics further show that the indexes of aggregate output and output of Iron ore, Chromium, Manganese and Diamonds have the highest maximum values, representing the upper bound of the data range, while the indexes of output of Other metals and Gold have the lowest minimum values. The indexes of aggregate output and output of Iron ore, Chromium, Manganese and PGMs have the highest means, or average, values, the indexes of the output of Copper and Gold have the lowest mean value, while the indexes of the output of Mining, Coal and Nickel were around the base value of 100. Recall that the indexes of the output of Iron ore, Chromium and Manganese increased the most, on average, between 2000 and 2024, the indexes of the output of Copper and Gold decreased the most, on average, between 2000 and 2024, while the indexes of the output of Mining and Coal did not change significantly. This implies that output of Iron ore, Chromium and Manganese grew the most, output of Copper and Gold declined the most, while output of Mining and output of Coal hardly changed significantly between 2000 and 2024. The indexes of the output of Mining and that of Coal have the lowest standard deviations, while the opposite is true for the indexes of the output of Copper and that of Gold, implying that output of Mining and that of Coal were closest to their mean values, which suggests their less variability during the sample period.

Aggregate, or economy wide, output, as well as aggregate output of the minerals industry, together with the disaggregated output of the minerals were transformed from annual frequency to quarterly frequency to increase the number of observations. The variables were then transformed to their Hodrick and Prescott (1997) trends by removing the cycle component. 8 quarters were forecasted at the end of each variable 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), Campbell and Mankiw (1987a), Campbell and Mankiw (1987b), Gordon (2007), Kydland and Prescott (1990), Romer (1993) and Stock and Watson (1999), while Hodrick and Prescott (1997), Christiano and Fitzgerald (2003) and Baxter and King (1999) provide the methodological aspects of decomposing the economic time series into its components. Decomposing the economic time series into its short term, also called cyclical or transitory, component, as well as long term, also called permanent or trend, components, facilitates the analysis of the relationship between *structural* minerals fluctuations and the macroeconomy.

Methodology

Bayesian Model Averaging (BMA) is used to analyse the relationship between *structural* minerals fluctuations and the macroeconomy, as discussed. Bayesian Model Averaging (BMA) was proposed by Leamer (1978), introduced by Bartels (1997) and is described in detail in Hoeting et al. (1999). This method emphasises variable importance when selecting the relevant variables in high dimensional data where information may usually be scattered through a large number of potential explanatory, or covariate, variables. Bayesian Model Averaging (BMA) accounts for the model uncertainty inherent in variable selection. The method also overcomes the omitted variable bias by averaging over the best models providing an optimal way to capture the underlying relationships between the variables. Thus, according to Hoeting et al. (1999), Bayesian Model Averaging (BMA) efficiently minimises the estimated parameters towards the stylised representation of the data leading to sound inference. According to Hinne et al. (2020), Bayesian Model Averaging (BMA), thus, combines predictions from multiple models, weighting each model by its posterior probability to account for model uncertainty, alternative to selecting a single "best" model, providing a more robust and reliable predictions.

The empirical Bayesian Model Averaging (BMA) model is specified following Feldkircher and Zeugner (2015), where the details on the the model structure can be found. Given a vector of the dependent variable y_t, which contains the structural components of aggregate, or economy wide, output, and a matrix of explanatory variables X_t, which contains the structural components of aggregate output of the minerals industry, together with disaggregated output of the minerals, Bayesian Model Averaging (BMA) model is specified as follows

$$y_t = \alpha_{\gamma t} + X_{\gamma t}\beta_{\gamma t} + \epsilon_t \quad , \quad \epsilon_t \sim N\left(0, \sigma^2\right) \tag{1}$$

where $\alpha_{\gamma t}$ is a constant, $\beta_{\gamma t}$ are coefficients, ϵ_t is the error term with mean 0 and variance σ^2. In the event of high dimensional data, the variable selection approach estimates all the possible combinations of X_{γ_t} and constructs a weighted average over them to circumvent the identification of the explanatory variables to include in the model. $X_{\gamma t}$, consequently, contains K variables, or structural components of the minerals, such that 2^K combinations of the variables are estimated, resulting in 2^K models.

The model weights for Bayesian Model Averaging (BMA) are derived from posterior model probabilities using Bayes theorem as follows

$$p\left(M_\gamma \mid y, X\right) p\left(M_\gamma\right) p\left(y \mid X\right) = p\left(y \mid M_\gamma, X\right) = \left(y \mid M_\gamma, X\right) p\left(M_\gamma\right) \sum_{\gamma=1}^{2^K} p\left(y \mid M_s, X\right) p\left(M_s\right) \tag{2}$$

where $p\left(M_\gamma \mid y, X\right)$ is the posterior model probability, M_γ is the true model, $p\left(y \mid M_\gamma, X\right)$ is the marginal likelihood of the model, $p\left(M_\gamma\right)$ is prior model probability and $p\left(y \mid X\right)$ is the constant integrated likelihood over all models. The Posterior Model Probability (PMP) is

$$p\left(y \mid X\right) p\left(\beta_\gamma \mid y, X\right) = \sum_{\gamma=1}^{2^K} p\left(\beta_\gamma \mid M_\gamma, y, X\right) p\left(M_\gamma \mid y, X\right) \quad (3)$$

where β_γ are the parameters of the model. The unconditional coefficients of the model are

$$E\left(\beta_\gamma \mid y, X\right) = \sum_{\gamma=1}^{2^K} p\left(\beta_\gamma \mid M_\gamma, y, X\right) p\left(M_\gamma \mid y, X\right) \quad (4)$$

where the Prior Model Probability (PMP) has to be proposed based on prior knowledge or believe. According to Varian (2014), Bayesian Model Averaging (BMA) analyses models with high dimensional data revealing interdependence among variables, resulting in better approximation to reality, hence the method leads to new ways to understand the underlying relationships between the variables.

Results

Bayesian Model Averaging (BMA) was used to analyse the relationship between *structural* minerals fluctuations and the macroeconomy, as discussed. Bayesian Model Averaging (BMA) uses Bayesian statistics hence it requires the specification of the prior distributions on the model parameters and the model space, the Markov Chain Monte Carlo (MCMC) sampler, the number of draws that the sampler runs, or iterations, and the number of the first iterations, or burnins, to be omitted from the estimation results, etc. The number of draws refers to the number of iterations that that the Markov Chain Monte Carlo (MCMC) sampler runs. Burn ins are the number of initial iterations to be omitted. The number of draws and burnins for the Markov Chain Monte Carlo (MCMC) sampler were set to 100000 and 10000, respectively. Markov Chain Monte Carlo (MCMC) is the Markov chain Monte Carlo sampler to be used in estimation. Model prior is the mass on model size and g Prior is the hyper parameter that determines the degree of prior uncertainty. The following pre estimation model statistics were selected for all estimations. The Markov Chain Monte Carlo (MCMC) sampler is Birth Death (BD), while the hyper parameter on Zellner (1986) g-prior is Benchmark, or BRIC. A uniform prior is specified, such that each possible model is assigned the same prior probability.

Model statistics of the relationship between *structural* minerals fluctuations and the macroeconomy are presented in Table 2 and Figure 3. Model space, or the number of possible statistical models, is 8192.0 given the aggregate output of the minerals industry, together with disaggregated output of about 12 minerals, where model space refers to the set of all possible models that can be created using the available predictors, or covariate variables. Mean number of regressors, which shows the average number of regressors with relatively high probability of inclusion across all the sampled models, is 11.3. Thus the models predicts about 11 covariate variables, on average, with high probability of inclusion in the estimated models. Posterior Model Probability (PMP) Correlation, which shows that the degree of convergence between the prior and the posterior model probabilities, is reasonably high for all the estimated models for aggregate output of the minerals industry and disaggregated minerals at almost 1.0. Shrinkage factor, which is a goodness of fit indicator, or the parameter g that affects how much the coefficients are shrunk towards zero, is 1.0, implying an almost perfect goodness of fit for the estimated models of aggregate output of the minerals industry and disaggregated minerals.

The results of the relationship between *structural* minerals fluctuations and the macroeconomy are presented in Table 3 below and Figure 4 in the Appendix. The correlation coefficients, denoted Cor, which measure the strength and direction of the linear association between the indexes of aggregate, or economy wide, output and the indexes of aggregate output of the minerals industry, together with the disaggregated output of the minerals are replicated from in Table 1 of descriptive statistics, where the interpretation is similar. PI Prob, which denotes Posterior Inclusion Probabilities (PIPs), is the sum of Posterior Model Probabilities (PMPs) for all models wherein a covariates of aggregate output of the minerals industry and disaggregated output of the minerals were included. Posterior Inclusion Probabilities (PIPs), thus, summarise the importance of each covariate across all possible models. Based on Posterior Inclusion Probabilities (PIPs), output of Mining, Coal, Iron.ore, Chromium, PGMs, Gold, Diamonds, Quarrying and Other non metals are included in about 100 percent of the models that explain aggregate output. Output of Copper and Manganese are included in about 99

Statistic		Statistic	
Model space	8192.00	Draws	10000.0
Mean regressors	11.3067	Burnins	1000.00
PMP correlation	1.00000	Top models	100.000
Shrinkage factor	0.99410	Model Prior	Uniform
Models visited	5679.00	g-Prior	BRIC
MP Size	6.50000	MCMC	BD

Notes: Own calculations with data from Statistics South Africa. Model space is the number of possible models, Mean regressors are the average number of regressors with high probability of inclusion, PMP correlation is the degree of convergence between the prior and the posterior model probabilities, Shrinkage factor is the goodness of fit indicator.

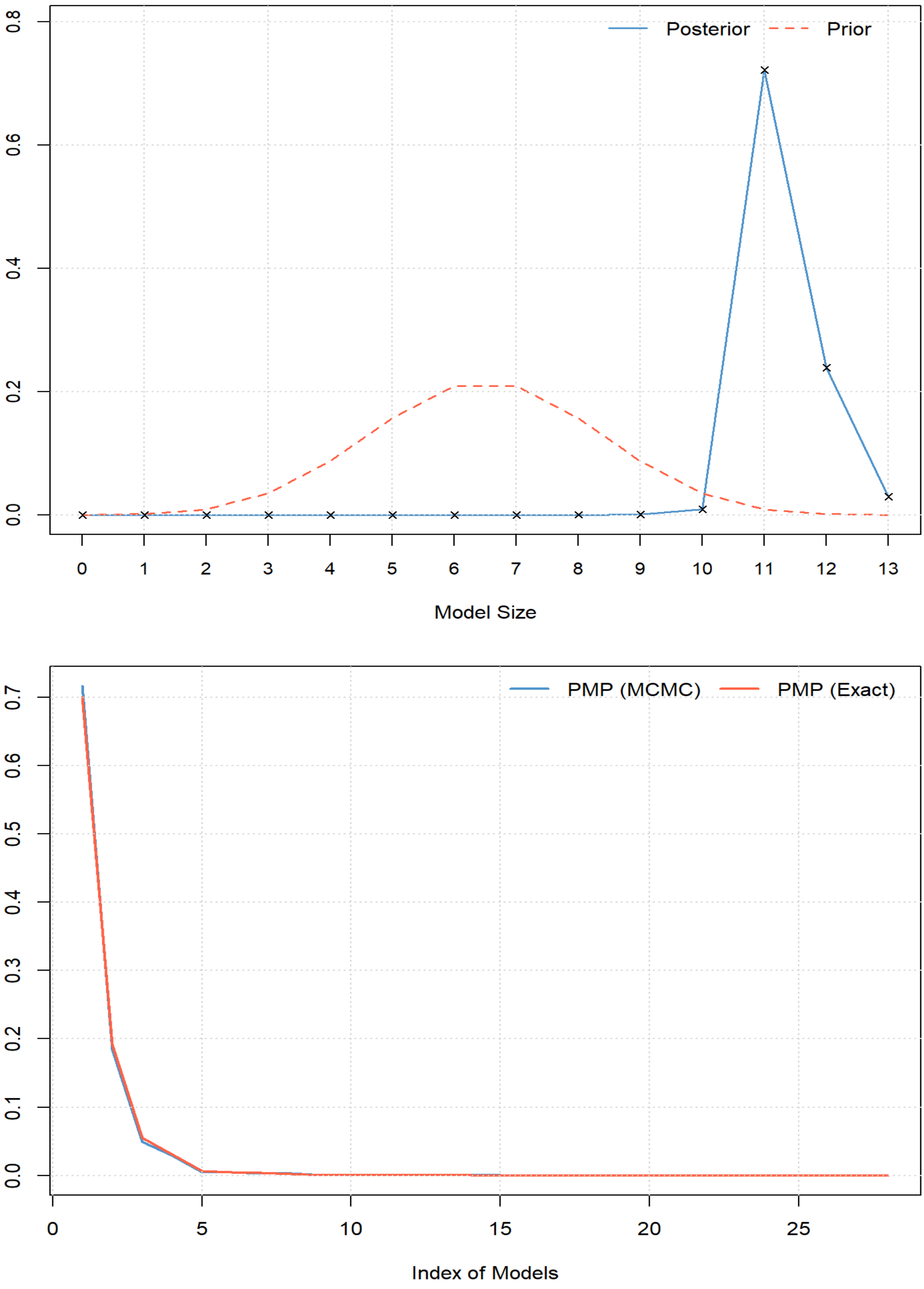
Table 2: Model statistics

percent of the models that explain aggregate output, respectively. Output of Nickel and Other metals are included in 20 percent, or less, of the models that explain aggregate, or economy wide, output.

Conditional Position Sign (CPS), denoted CP Sign, is the posterior expected value, or probability, of a positive coefficient conditional on inclusion of a covariate in the estimated models, or respectively sign certainty. The Conditional Position Signs (CPSs) show a strong probability of a positive relationship between aggregate, or economy wide, output and output of Mining, Chromium, Manganese, Other metals and Quarrying. In contrast, the corresponding Conditional Position Signs (CPSs) show a near to zero probability of a positive relationship between aggregate, or economy wide, output and output of Coal, Iron ore, Copper, PGMs, Gold, Diamonds and Other non metals, hence in virtually all models that include these covariates, the coefficient signs are negative. The Conditional Position Signs (CPSs) further show mixed probability of a positive relationship between aggregate, or economy wide, output and output of Nickel, such that all models that include these covariates have inconclusive coefficient signs. Output of Nickel has, to a certain degree, predominantly positive Conditional Position Signs (CPSs). The Posterior Model Probabilities (PMPs) show that output almost all the disaggregated minerals have a relationship with aggregate, or economy wide, output, while Conditional Position Signs (CPSs) show that such relationship is predominantly negative.

Post Mean and Post SD denote Posterior Mean and Posterior Standard Deviation (PSD), respectively. Bayesian Model Averaging (BMA) averages the coefficient estimates from all considered models, weighted by their posterior probabilities, instead of selecting a single best model, which introduces uncertainty, as different models may yield different estimates for the same parameter. Posterior Mean is the expected value of a parameter after averaging over all possible models, including the models wherein the variable was not contained implying that the coefficient is zero, weighted by their respective posterior probabilities. The Posterior Means show that a 1 percentage point increase in output of Chromium and Quarrying is associated with 0.2 percentage point and 0.3 percentage point increase in aggregate, or economy wide, output, respectively, while the rest of the covariates have near zero coefficients. The coefficient signs are also consistent with the Conditional Position Signs (CPSs), discussed above. Posterior Standard Deviation (PSD) quantifies uncertainty in parameter estimates after averaging across multiple models, reflecting variation of estimated parameter values depending on the chosen specification, providing insight into the robustness and reliability of the estimates.

The empirical results have revealed interesting relationships between *structural* minerals fluctuations and aggregate, or economy wide, output. The results have shown that output of Mining, Coal, Iron.ore, Chromium, PGMs, Gold, Diamonds, Quarrying and Other non metals are included in about 100 percent of the models that explain aggregate, or economy wide, output, that Copper and Manganese are included in about 99 percent of the models that explain aggregate output and that output of Nickel and Other metals are included in 20 percent, or less, of the models that explain aggregate output, based on Posterior Inclusion Probabilities (PIPs) across all possible models. The results have also shown a strong probability of a positive relationship between aggregate, or economy wide, output and output of Mining, Chromium, Manganese, Other metals and Quarrying, a near to zero probability of a positive relationship between aggregate output and Coal, Iron ore, Copper, PGMs, Gold, Diamonds and Other non metals and a mixed probability of a positive relationship between aggregate output and output of Nickel, based on Conditional Position Signs (CPSs). The



Notes: Own calculations with data from Statistics South Africa. Model size is the variables in a specific model, while Index of models are models with the best likelihoods. PMP (MCMC) are Posterior model probabilities when using a Markov Chain Monte Carlo (MCMC) sampling, while PMP (Exact) are those when enumerating all possible models.

Figure 3: Model statistics

coefficient signs of the Posterior Means are consistent with the Conditional Position Signs (CPSs).

Although macroeconomics is not prescriptive about the transitory and structural relationship between aggregate, or economy wide, output and output of aggregate minerals industry, together

	Cor	PI Prob	Post Mean	Post SD	CP Sign
Mining	-0.577614	1.000000	2.250829	0.334819	1.000000
Coal	0.482924	1.000000	-0.448500	0.055764	0.000000
Iron.ore	0.907104	0.997590	-0.331575	0.070913	0.000000
Chromium	0.903293	1.000000	0.535895	0.079029	1.000000
Copper	-0.926735	0.988710	-0.287036	0.084597	0.000030
Manganese	0.880820	0.993220	0.212272	0.045447	1.000000
PGMs	0.050931	0.999650	-0.468362	0.111538	0.000000
Nickel	0.126303	0.101110	-0.005163	0.039586	0.579666
Other.metals	-0.528557	0.222570	0.036667	0.088060	0.995732
Gold	-0.986601	1.000000	-1.058262	0.078551	0.000000
Diamonds	-0.646000	1.000000	-1.466414	0.236033	0.000000
Quarrying	0.675482	1.000000	0.900072	0.096267	1.000000
Other.non.metals	-0.906734	1.000000	-0.616510	0.081253	0.000000

Notes: Own calculations with data from Statistics South Africa. Cor is the correlation coefficient of the selected variable, PI Prob is the Posterior Inclusion Probability (PIP), Post Mean is posterior mean, Post SD is the associated Posterior Standard Deviation (PSD), while CP Sign is the Conditional Position Sign (CPS) of the selected variable.

Table 3: Model results of the structural components

with disaggregated minerals, according to Diebold and Rudebusch (1970) and Romer (1993), different economic sectors do not respond in a similar manner to economic fluctuations. The structural component, or long term periodicity, of output of aggregate Mining is cyclical. This means that Mining performance, and by implication, profitability, fluctuates in patterns, often consistent with the broader economic cycles, such that it shows a discernible relationship with fluctuations of the aggregate economy. Output of Chromium, Manganese and Quarrying are procyclical. Output of Coal, Iron Ore, Copper, PGMs, Gold, Diamonds and Other non metals are countercyclical. Output of Nickel and Other metals is acyclical, hence its fluctuations are inconsistent with the broader economic cycles. As discussed, common fluctuations between economic sectors and industries could be because they are driven by common shocks, or economic events that affect multiple sectors simultaneously, emanating from factors that include economic policies, investment and consumption decisions.

Conclusion

This paper analysed the *structural* relationship between minerals fluctuations and the macroeconomy in South Africa. This was achieved by isolating the trend component of aggregate output of the minerals industry, together with output of disaggregated minerals and comparing their fluctuations with the trend component of aggregate, or economy wide, output. The results have shown a significant, and predominantly positive, or procyclical, relationship between aggregate output and output of Mining, at structural, or long term, periodicities. The results have also shown a significant relationship between aggregate output and output of Coal, Iron.ore, Chromium, Copper, Manganese, PGMs, Gold, Diamonds, Quarrying and Other non metals, while they show an insignificant relationship between aggregate output and output of Nickel and Other metals. The results have further shown a positive, or procyclical, relationship between aggregate output and output of Chromium, Manganese, Other metals and Quarrying, a mixed relationship between aggregate output and output of Nickel, while they also show a negative, or countercyclical, relationship between aggregate, or economy wide, output and output of Coal, Iron ore, Copper, PGMs, Gold, Diamonds and Other non metals.

The results have generally shown that, at long term periodicities, output of the minerals industry and disaggregated minerals do not respond in a similar manner to economic fluctuations. As discussed, *structural* economic fluctuations are driven by changes in the fundamental structure of the economy, such as changes in government policy and consumer preferences, technological advancements, shifts in demographics, changes in resource availability and globalisation, hence they are associated with supply side economics, which focuses on increasing increasing production, or supply of goods and services. A comprehensive determination of the temporal relationship between the minerals industry and different macroeconomic indicators to inform targeted sector specific policy making, where appropriate, is recommended. Several economic indicators, such as the monetary policy interest rate, government expenditure and taxation, foreign direct investment, prices of commodities and financial assets, foreign exchange rates as well as foreign demand and geopolitics, affect output of the minerals industry, together that of disaggregated minerals, at least theoretically, hence it's important for future research to analyse the common movement between these economic indicators and the minerals industry.

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Appendix

Appendix 1. Description of the variables

The detailed descriptions of the variables are presented in Table 4 below.

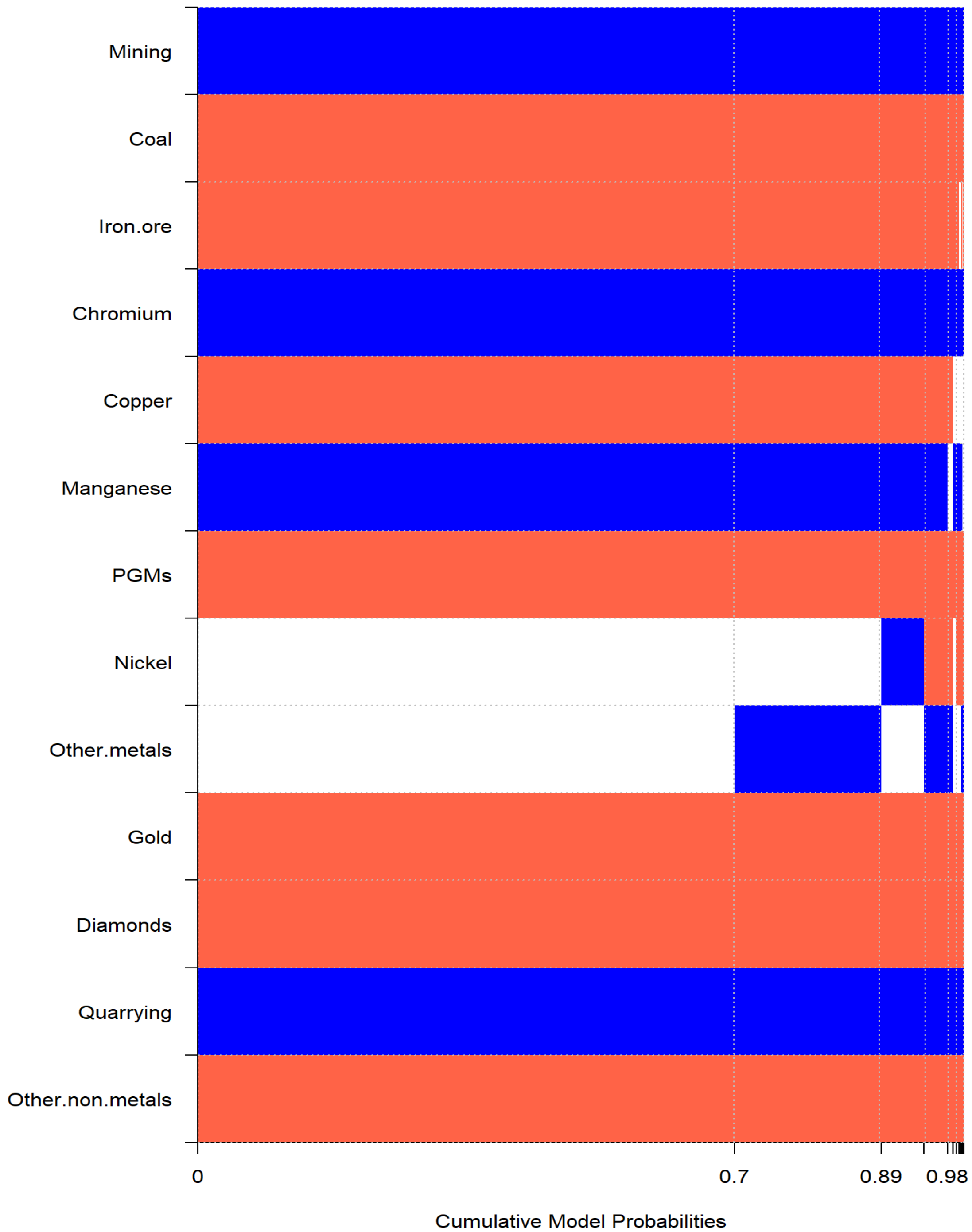
Denotation	Variable	Description
Coal	Coal	Mining of anthracite, bituminous coal, brown coal and lignite
Iron ore	Iron ore	Mining of iron ore, titaniferous iron ore, magnetite and iron sand
Chromium	Chrome ore	Mining of Chromite, also known as chrome ore, the main source of chromium
Copper	Copper	Mining of copper ore, a reddish brown, malleable and ductile source of copper
Manganese	Manganese	Mining of minerals with manganese compounds, primarily oxides and carbonates
PGMs	Platinum Group Metals	Mining of Platinum Group Metals (PGMs) including platinum, palladium and osmium
Nickel	Nickel	Mining of nickel, a silvery white lustrous metal with a slight golden shade
Other.metals	Other metallic minerals	Mining of all other metal related minerals, not elsewhere classified
Gold	Gold	Mining of mining of gold and uranium ores, often found together in ore deposits
Diamonds	Diamonds	Mining and alluvial diggings od diamonds, a crystalline form of the element carbon
Quarrying	Building materials	Mining of of building and monumental stone, including ceramic, sand and gravel
Other.non.metals	Other non metallic minerals	Mining of all other non metal related minerals, not elsewhere classified

Notes: Data from Statistics South Africa. Detailed minerals descriptions of the major divisions and major groups can be found in Statistics South Africa's Standard Industrial Classification (SIC) Major Division 2: Mining and Quarrying

Table 4: Variables description

Appendix 2. Plots of model results

Selected model diagnotic statistics are depicted in Figure 4 below and complement model statistics.



Notes: Data from Statistics South Africa. Cumulative model probabilities sum Posterior Model Probabilities (PMPs).

Figure 4: Model probabilities