Predicting South African Equity Premium using Domestic and Global Economic Policy Uncertainty Indices: Evidence from a Bayesian Graphical Model[#]

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Abstract

This paper analyses whether we can predict South African excess stock returns based on a measure of economic policy uncertainty (EPU) of South Africa and twenty other developed and emerging markets. In this regard, we use a Bayesian graphical model estimated over the sample period of 1998:01-2012:12. The model is also estimated in a rolling-window fashion over the monthly sample period of 2003:01-2012:03, using an initial sample period of 1998:01-2002:12. The Bayesian shrinkage approach allows us to simultaneously model the 21 EPUs, over and above 22 other standard

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financial and macroeconomic predictors. In addition, the Bayesian graphical model also provides both instantaneous and lagged relationships between the predictors and the equity premium. Our full sample results show that, in terms of instantaneous relationship, none of the EPUs play any role, and for the lagged relationship, only the EPU of Hong Kong and the Netherlands can be considered as important with posterior inclusion probabilities in excess of 0.50. Rolling estimates show that instantaneous relationships are quite constant and do not indicate any significant links from EPUs to the equity premium. On the other hand, rolling estimates are highly time-varying, and there is significant lagged impact from most of the EPUs in various sub-periods.

Keywords: Economic Policy Uncertainty; Stock Prices; Prediction; Bayesian Graphical Models; Vector Autoregression; South Africa
JEL Classification: C32; C53; E60; G12; G17

1- Introduction

On one hand, predictability of stock returns is important for practitioners in finance for asset allocation. On the other hand, academics in finance are interested in stock return predictability, since it has important implications for tests of market efficiency, which in turn, helps to produce more realistic asset pricing models (Rapach *et al.*, 2013; Rapach and Zhou, 2013; Neely *et al.*, 2014). However, stock return prediction is highly challenging, since it inherently contains a sizable unpredictable component (Rapach and Zhou, 2013). Not surprisingly, the international evidence of predicting stock returns is highly varied, with results contingent on models, variables, sample period and countries under consideration (see Aye *et al.*, (forthcoming) for a detailed literature review in this regard). In line with the international literature, the evidence for South African stock returns (our case study in this paper), based on domestic and international macroeconomic and financial variables, is mixed as well. While studies like, Gupta and Modise (2012a, b, 2013), Aye *et al.*, (2013), Wen *et al.*, (2015), and Sousa *et al.*, (2016) finds very limited evidence of stock returns predictability; Gupta *et al.*, (forthcoming) and Balcilar *et al.*, (forthcoming) respectively, finds that stock return is predictable to a certain degree, when Bayesian predictive regressions (which uses many predictors simultaneously in the predictive regression model) and nonparametric quantile methods are employed.

Our primary focus in this paper is the recent study by Balcilar *et al.*, (forthcoming), which analyze stock returns predictability based on news-based measures of economic policy uncertainty (EPU) developed by Brogaard and Detzel (2015). Note that, Brogaard and Detzel (2015) perform month-by-month searches of newspapers for terms related to economic and policy uncertainty to construct their measure of EPU. Balcilar *et al.*, (forthcoming) use a bivariate (involving stock returns and EPU of a specific country) nonparametric causality-in-quantiles approach to show that the EPU of South Africa and twenty other developed and emerging markets causes South African stock returns over its entire conditional distribution, with the same being strongest around the median.

Against this backdrop, the objective of our paper is to analyse the importance of the Brogaard and Detzel's (2015) news-based EPU of South Africa, as well as, the EPUs of twenty other developed and emerging markets

(Australia, Brazil, Canada, China, France, Germany, Hong Kong, India, Italy, Japan, Malaysia, Mexico, The Netherlands, South Korea, Spain, Sweden, Switzerland, UK and US), modelled together along with other domestic and international and macroeconomic and financial variables can predict South African excess stock returns (equity premium). Put alternatively, our aim is to check if the recent evidence provided by Balcilar *et al.,* (forthcoming) of stock returns predictability based on EPUs in a bivariate-setting continues to hold when we incorporate the information of the 21 EPUs and other important financial and macroeconomic predictors (used in this literature internationally and for South Africa) simultaneously. In other words, we want to verify if the results of Balcilar *et al., (forthcoming)* could possibly due to omitted variable bias. In this regard, we use the Bayesian graphical model developed recently by Ahelegbey *et al.,* (forthcoming) estimated over the full sample period of 1998:01-2012:03, and over a sixty-months rolling window-based sample period of 2003:01-2012:03 using an initial sample of 1998:01-2002:12, with the samples governed by data availability. The Bayesian graphical approach uses shrinkage estimation that allows us to prevent the issue of overparametrization involved in modelling simultaneously 43 predictors, and hence prevent possible omitted variable bias that is likely to exist in the bivariate approaches. In addition, the approach also allows us to study both contemporaneous and lagged relationships from the predictors to the equity premium, and detect the importance (based on posterior probabilities of inclusion) of each of the individual predictors even when modelled in a multivariate framework. In the process, our paper adds to a recent (but growing) literature, which analyses the role of EPU in predicting stock returns. In this regard, some mixed, primarily in-sample, empirical evidence besides the already discussed Balcilar *et al.*, (forthcoming), can be found in Antonakakis *et al.*, (2013), Bhagat *et al.*, (2013), Kang and Ratti (2013), Gupta *et al.*, (2014), Bekiros, Gupta and Majumdar (2015), Brogaard and Detzel (2015), Chang et al., (2015), Chuliá *et al.,* (2015), Jurado et al., (2015), Kang and Ratti (2015), Mensi *et al.*, (2014), Redl (2015), Sum (2012a, 2012b, forthcoming), Balcilar, Gupta, Kim and Kyei (2015), Momim and Masih (2015), Rossi and Sekhposyan (2015), Bekiros, Gupta and Kyei (forthcoming), Li *et al.,* (forthcoming) and Mensi, Hammoudeh, Yon and Nguyen (forthcoming).[1] In general, based on the literature relating stock

[1] While, there exists no clear-cut consensus in terms of whether to use a structural model based approach (Mumtaz and Zanetti, 2013; Alessandri and Mumtaz, 2014; Mumtaz and Surico, 2013; Carriero *et al.,* 2015; Chuliá *et al.,* 2015; Mumtaz and Theodoridis, 2014, 2015; Jurado

returns and uncertainty, we can make the following observations: (a) Uncertainty tends to predict not only stock returns, but also its volatility; though the evidence is mixed with results depending on methodology, country and sample period; (b) Higher levels of uncertainty is found to dampen stock returns, but also simultaneously make the market more volatile; (c) The relationship between uncertainty and the stock market is better depicted by nonlinear models rather than its linear counterparts; (d) Nonlinearity seems to be especially important when forecasting the stock market out-of-sample, and; (e) Uncertainty tends to affect stock markets irrespective of whether it is in a developed or developing/emerging country. Overall, the impact of uncertainty on equity market cannot be underestimated, as the recent financial crisis can vouch for.

A relevant question, which we have been silent so far, but needs to be asked is: What is the theoretical background that causes one to believe that EPU (both domestic and global) can predict stock returns? In this regard, there are direct and indirect channels through which uncertainty can affect the stock market. In terms of the direct route, Bloom (2009) develops a standard firm-level model with a time-varying second moment of the driving process and a mix of labor and capital adjustment costs. Then the author shows that firms only hire (fire) and invest (disinvest) when business conditions are sufficiently good (bad). In addition, the model yields a central region of inaction in hiring and investment space (due to nonconvex adjustment costs), which in turn, expands when uncertainty is high, with firms becoming more cautious in responding to business conditions. As far as the indirect channel is concerned, we must realize that asset returns are functions of the state variables of the real economy, and the real economy itself displays significant fluctuations. Besides standard theoretical justifications of such fluctuations based on productivity and/or policy shocks, a recent strand of literature relates the impact of various forms of policy-generated uncertainty, to movements in macroeconomic variables (Bloom, 2009; Aastviet *et al.*, 2014; Colombo,

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et al., 2015; Rossi and Sekhposyan, 2015) or a news-based method (Baker *et al.*, 2015; Brogaard and Detzel, 2015) to construct measures of uncertainty, the latter seems to have gained tremendous popularity in various applications of macroeconomics and finance (see Redl (2015) and Strobel (2015) for detailed reviews). This is most likely due to the fact that data (not only for the US, but also other European and emerging economies) based on newspaper articles is easily and freely available for use, and does not require any complicated estimation of a model to generate it in the first place.

2013; Jones and Olson, 2013, Mumtaz and Zanetti, 2013; Karnizova and Li, 2014; Alessandri and Mumtaz, 2014; Mumtaz and Surico, 2013; Balcilar *et al.,* 2014, 2015; Carriero *et al.,* 2015; Chuliá *et al.,* 2015; Mumtaz and Theodoridis, 2014, 2015; Jurado *et al.,* 2015; Redl, 2015; Rossi and Sekhposyan, 2015), which in turn, is expected to affect stock returns.[2] While, this explanation relates to the role a South Africa's EPU can play in affecting its own stock returns, as depicted by Redl (2015), and Balcilar *et al.,* (forthcoming), we also need to understand why EPU of other countries might predict South African stock returns? The explanation in this regard, emanates from the following lines of thinking: South Africa, along with the other BRIC countries, is the major recipient of global investment flows. As changes in the EPU of a specific foreign country would affect that economy's domestic and global investment potential, it is likely to feed into South Africa's growth process and its stock markets (Balcilar, Gupta, Kim and Kyei, 2015; Balcilar *et al.,* forthcoming). Moreover, international investors are interested in South African stock market (besides the BRICs) for risk diversification opportunities, which in turn, provides a direct channel through which a changes in the EPU of a foreign nation, can affect South African stock returns (Balcilar, Gupta, Kim and Kyei, 2015; Balcilar *et al.,* forthcoming). In other words, foreign EPUs are expected to affect South African stock returns, given the increased economic integration of the South Africa with the world economy. To the best of our knowledge, this is the first attempt to predict South African stock returns using a Bayesian graphical approach. The remainder of the paper is organized as follows: Section 2 provides a brief description of the Bayesian graphical model, while Section 3 presents the data and the results. Finally, Section 4 concludes.

2 – Methodology

The main objective of this paper is to model the contemporaneous and lagged dependence/causality between the equity premium of South Africa and 43 possible predictors over an full-sample and rolling sub-samples. A multivariate system of equation such as a structural vector autoregressive

[2] For detailed theoretical explanation in general equilibrium models relating policy uncertainty to stock market movements, the reader is referred to Pástor and Veronesi (2012, 2013).

(SVAR) represented in equation (1) below can be used to model this dependence/causality:

$$Y_t = B_0 Y_t + \sum_{i=1}^{p} B_i Y_{t-i} + \sum_{i=1}^{p} C_i Z_{t-i} + \varepsilon_t \qquad (1)$$

where $t = 1, \dots, T$ and p is the maximum lag order. Y_t and Z_t are n_y and n_z vector of response (excess stock returns) and predictor variables, respectively. ε_t is n_y vector of structural disturbances which are independently, identically $(i.i.d)$ and normally distributed with mean zero and covariance matrix Σ_ε ; B_0 is a $(n_y \times n_y)$ zero diagonal matrix of structural contemporaneous coefficients, with zero diagonals; B_i and C_i with $1 \le i \le p$ are $(n_y \times n_y)$ and $(n_y \times n_z)$ matrices of the parameters of interest, respectively. For easy notation, we rewrite the reduced form of equation (1) in matrix form as follows:

$$Y_t = A_1 X_{t-1} + \ . \ . \ . \ A_p X_{t-p} + u_t \qquad (2)$$

where $X_t = (Y_t, Z_t)' = (X_{1t}\ ,\ X_{2t}, .\ .\ .\ ,\ X_{nt})'$ is an $n = n_y + n_z$ dimensional time series; $B_i^* = (B_i, C_i)$, $1 \le i \le p$, are $(n_y \times n)$ matrices of unknown coefficients; $A_0 = (I_{n_y} - B_0)$ is a $(n_y \times n_y)$ matrix; $A_i = A_0^{-1} B_i^*$, $1 \le i \le p$, are $(n_y \times n)$ reduced-form lag coefficient matrices; and $u_t = A_0^{-1}\varepsilon_t$ is an $(n_y \times 1)$ $i.i.d$ reduced-form vector error term with zero mean and covariance matrix Σ_u. Empirically the parameters of this SVAR model cannot be directly estimated due to the problems of over- and/or under-identification of the system of equations. The parameters of the SVAR are obtained either by obtaining a reduced form equation (2) or by imposing a certain number of restrictions on the coefficients of the contemporaneous variables. It is often difficult to provide convincing restrictions without relying on theories which undermines the objective of SVAR to empirically assess theoretical hypothesis (Ahelegbey *et al*., forthcoming). To overcome these difficulties; this paper uses the Bayesian Graphical Vector Autoregressive (BGVAR) model proposed by Ahelegbey *et al*. (forthcoming).

This paper applies the Dynamic Bayesian Network technique[3] to the conventional SVAR model exhibited in equation (1). The BGVAR model has the following advances over the conventional SVAR model: no need to obtain the reduced form, no need to impose restrictions on the contemporaneous variables; and most importantly the BGVAR model decomposes the SVAR causality structure into two simple representations: the Contemporaneous Network (CN) and the Lagged Network (LN) causality structures as shown in equation (3) below, which in turn, can be evaluated over an out-of-sample.

Let $X_t = (X_t^1, X_t^2, \ldots, X_t^n)$ denote the vector of realized values of n variables with X_t^i representing the realization of the i-th variable. Equation (1) can be represented as a dynamic graphical model where there exists a one-to-one correspondence between the coefficient matrices of the SVAR in equation (1) and directed acyclic graph (DAG):

$$X_{t-s}^j \longrightarrow X_t^i \Leftrightarrow B_{s,ij}^* \neq 0, \quad 0 \leq s \leq p \tag{3}$$

where $B_0^* = B_0$ for $s = 0$ and $B_s^* = (B_s \, C_s)$ for $0 \leq s \leq p$. Considering the SVAR in equation (1), the DAG model can be represented as:

$$Y_t = \underbrace{(G_0 \circ \Phi_0)}_{CN} Y_t + \sum_{i=1}^{p} \underbrace{(G_i \circ \Phi_i)}_{LN} X_{t-i} + \varepsilon_t \tag{4}$$

where "$\circ$"is the Hadamard product. In equation (4), coefficient matrices of the SVAR in equation (1) are represented as:

$$B_s^* = (G_s \circ \Phi_s), \qquad 0 \leq s \leq p, \tag{5}$$

where for $s = 0$, $B_0^* = B_0$, G_0 is an $(n_y \times n_y)$ a binary connectivity matrix of contemporaneous dependence, and Φ_0 is an $(n_y \times n_Y)$ coefficient matrix with elements $\phi_{ij} \in R$. For $1 \leq s \leq p$, Φ_s are a $(n_y \times n)$ matrices of regression coefficients, and G_s are $(n \times n)$ matrices whose entries are:

[3] The Dynamic Bayesian Network is a technique which relates variables to each other over adjacent time steps. For more details interested readers are referred to Dagum et al., (1992).

$$g_{ij} = 1 \iff X_{t-s}^{j} \longrightarrow X_t^i \tag{6}$$

Meaning that there is a one –to–one correspondence between regression matrices and the directed acyclic graphs[4]. Finally Φ_s, $1 \leq s \leq p$, are $\left(n_y \times n\right)$ matrices of coefficients with elements $\phi_{ij} \in R$.

Ahelegbey *et al.*, (forthcoming) show that the LN component can be estimated by making use of a Bayesian scheme with an efficient Markov Chain Monte Carlo (MCMC) process as in Grzegorczyk *et al.*, (2010). However, for the CN, Ahelegbey *et al.*, (forthcoming) propose a necessary and sufficient condition to check the acyclicity[5] constraint in a small-size networks as suggested by Giudici and Castelo (2003).

Let $b_i = (b_{i1}\ ,\ b_{i2}\ , \ldots , b_{in})$ be a row vector of B_s; its entries b_{ij} are the regression coefficients of the effects of X_{t-s}^{j} on X_t^i. Therefore, the relationship between B_s and Φ_s can be given by:

$$b_{ij} = \begin{cases} \phi_{ij} & \text{if} \quad g_{ij} = 1 \\ 0 & \text{if} \quad g_{ij} = 0 \end{cases} \tag{7}$$

Following Ahelegbey *et al.*, (forthcoming) the marginal prior of g_{ij} is assumed to be a Bernoulli distribution, and the marginal posterior is Bernoulli-distributed as well:

$$a_{ij}|data = \begin{cases} 1 & \text{if} \quad P\left(a_{ij} = 1|data\right) > \tau \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where τ is a threshold value set by the user $\tau \in (0, 1)$; and $P\left(a_{ij} = 1|data\right)$ is the confidence score i.e. the posterior probability of the existence of an edge from X^j to X^i.

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[4] See Murphy (2002).

[5] For more details, see more Murphy (2002).

3 – Data and Results

Our analysis is based on monthly data covering the period of 1998:01-2012:03, with the start and end-points being primarily driven by data availability on the EPU indices of South Africa and 20 other developed and emerging markets. The following variables were used in our analysis:

Equity premium: Our response variable, defined as nominal return on a stock market index (All-share index) in excess of the risk-free interest rate (the Treasury bill rate);

Following the stock returns predictability literature of South Africa discussed in the introduction, we use the following variables as our predictors, which in turn, are transformed to induce stationarity, except for the EPUs, which are already stationary in their natural logarithmic form:

Financials share prices: Real stock returns for the financial sector in South Africa, computed as the first difference in the log-levels of real Financial Stock Index;

Resources share prices: Real stock returns for the resource sector in South Africa, computed as the first difference in the log-levels of real Resource Stock Index;

Industrial share prices: Real stock returns for the industries in South Africa, computed as the first difference in the log-levels of real Industrial Stock Index;

Price-earnings ratio (log-level): One-year moving sum of the ratio of nominal earnings to nominal stock prices;

Price-dividend ratio (log-level): One-year moving sum of the ratio of nominal dividend to nominal stock prices;

Relative 90 days Treasury bill rate: Difference between the 90-day Treasury bill rate and a 12-month backward-looking moving average;

Term spread: Difference between long-term government bond yield and the 90-day Treasury bill rate;

Relative money market rate: Difference between the prime rate and the 12-month backward-looking moving average;

DAX: The nominal stock returns for Germany, computed as the first difference of the nominal natural logarithm of the DAX (Deutscher Aktien-Index) – a blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange;

CAC: The nominal stock returns for France, computed as the first difference of the nominal natural logarithm of the CAC 40 (the benchmark French stock market index);

S&P 500: The nominal stock returns for the US, computed as the first difference of the nominal natural logarithm of the S&P 500, which is the free-float capitalisation-weighted index of the prices of 500 large-cap common stocks;

FTSE 100: The nominal stock returns for the United Kingdom, computed as the first difference of the nominal natural logarithm of the FTSE 100 all-share index, which is a capitalisation-weighted index of around 100 companies traded on the London Stock Exchange;

NIKKEI: The nominal stock returns for Japan, computed as the first difference of the real Nikkei 225 stock index for the Tokyo Stock Exchange;

Hang-Seng: The nominal stock returns for Hong Kong, computed as the first difference of the nominal natural logarithm of the Hang Seng Index, which is a free float-adjusted market capitalisation-weighted stock market index;

Shanghai Stock Exchange (SSE): The nominal stock returns for China, computed as the first difference of the nominal natural logarithm of the Shanghai Stock Exchange (SSE) Composite index. SSE Indices are all calculated using a Paasche weighted composite price index formula. This means that the index is based on a base period on a specific base day for its calculation. The base day for SSE Composite Index is December 19, 1990, and the base period is the total market capitalization of all stocks of that day;

Real effective exchange rate: First difference in log-levels of real effective exchange rate index;

Narrow money supply growth rate: First difference in the log-levels of nominal narrowly defined money stock (M1A[6] and M1[7]);

Broad money supply growth rate: First difference of the log-levels of nominal broadly defined money stock (M2[8] and M3[9]);

Manufacturing production growth rate: First difference of the log-levels of manufacturing production;

Employment growth rate: First difference of the log-levels of employment in the non-agricultural sectors;

EPU: The data on natural logarithms of EPU for the 21 countries is derived from Brogaard and Detzel (2015).[10] The authors construct the EPU indices based on data from an internet search and count of articles that use key words associated with economic policy uncertainty in these countries. The source for their data is the Access World News database.

Below in Table 1, we present the posterior probabilities of full-sample estimates for the 43 predictors for both multivariate instantaneous (MIN) and multivariate autoregressive (MAR) structures. The lag order of the VAR is set to 1 based on the full sample data using the Bayesian Information Criterion, and 40,000 draws are used, with an initial burn-in of 10,000 from 50,000 draws to derive the posterior inclusion probabilities of the predictors. As far as instantaneous relationship is concerned, the highest posterior probabilities are for the sectoral stock returns (over 0.65), followed by the UK stock returns and the real effective exchange rate (greater than or equal to 0.40, but less than 0.50). Other standard variables that are found to be important are the

[6] M1A is defined as: currency (notes and coins) held by the public plus cheque deposits (held by monetary institutions) plus transmission deposits (held by monetary institutions).
[7] M1 is defined as: M1A plus other demand deposits held by monetary institutions.
[8] M2 is defined as: M1 plus short-term (up to 3 months) deposits plus medium-term (between 3 months and 1-year) deposits held by monetary institutions.
[9] M3 is defined as: M2 plus long-term (1-year and longer) deposits held by monetary institutions.
[10] We thank Jonathan Brogaard for providing us with the EPU data. Note that, though Brogaard and Detzel (2015) created the EPU for 21 countries in an earlier version of the paper, they only concentrated on the US stock market in the published version.

price-earnings ratio, the price-dividend ratio, the relative money market rate and the stock returns of France and the US. Amongst the uncertainty measures, the EPU of Australia and China are found to be relatively important. All these variables have posterior probabilities of between 0.30 and 0.39. While 13 other uncertainty indices (including that for South Africa) have posterior probabilities that are greater than 0.20, but less than 0.30. The Hong Kong and the Chinese stock returns, M1A and M3 growth rates, the relative Treasury bill rate and the term-spread also falls within this category. Remainder of the variables, including six other EPUs have posterior probabilities of less than 0.20.

Next we turn to the lagged relationship. Here the stock returns of Hong Kong and Japan, the term-spread, and the EPUs of Hong Kong and the Netherlands have posterior inclusion probabilities that are greater than or equal to 0.60. These 5 variables are, thus, the most important predictors of the South African equity premium. The stock returns on the financial sector, the German and UK stock markets, M3 growth rate, the relative money market rate, employment growth, and the EPUs of China, France and India follows the above 5 predictors in terms of importance with posterior probabilities greater than or equal to 0.40, but less than 0.50. With posterior probabilities greater than or equal to 0.30, but less than 0.40, there are as many as 11 EPUs (Brazil, Italy, Japan, South Korea, Malaysia, Mexico, Russia, Spain, Switzerland, UK and US), which serve as predictors for the equity premium. In the same category, we have the stock returns of the US, France, China, the growth rates of M1A, M1 and M2, the relative Treasury bill rate and the manufacturing production growth rate. All the remaining EPUs of Australia, Canada, Germany, South Africa and Sweden have posterior probabilities of less than 0.30, but greater than 0.20. Within the same category are resources and industrial sectoral returns, price-earnings ratio, price-dividend ratio, and real effective exchange rate. This implies that under the MAR structure, there are no variables which have posterior probability that is less than 0.20, unlike that of the MIN structure.[11]

[11] We also considered the payout ratio (the ratio of price-earnings to price-dividend) and inflation as predictors. However, due to high degree of multicollinearity between the pay-out ratio and the valuation ratios (price-earnings and price-dividend ratios), and between inflation and measures of money growth rates, the BGVAR algorithm broke down. However, when we replaced the two valuation ratios by the payout ratio, and all the measures of money growth rates by the inflation rate, the posterior probabilities of the payout ratio and the inflation rate

However, following Ahelegbey *et al.*, (forthcoming), the variables that are considered to be the selected edges of the MIN and MAR structures are those variables that have a posterior probability that is in excess of 0.50. If this is taken into account, the only variables that are important under the MIN structure are the three sectoral returns. While, under the MAR structure, only the EPUs of Hong Kong and the Netherlands, the Hang Seng and NIKKEI stock returns, and the term spread can be considered as important predictors for the excess returns of South Africa. In general, evidence in favour of excess returns predictability is weak, just like the majority of studies on this topic for South Africa. Note that, though it is true, that all the remaining EPUs have posterior probabilities that are greater than 0.20, but less than 0.50, it is only the EPU of Hong Kong and the Netherlands that can be considered as relevant – a result in contrast to that of Balcilar *et al.*, (forthcoming). This result is most likely due to two important differences between two studies. First, Balcilar *et al.*, (forthcoming) use a nonparametric quantile based method that is robust to nonlinearities, outliers, and structural breaks. Second, although the BGVAR model is linear, it controls for several other financial and macroeconomic predictors, as well as all 21 EPUs simultaneously in the model, and hence, is less likely to suffer from omitted variable bias.

Table 1. Posterior Probabilities of Predictors:

Variables	Multivariate Instantaneous (MIN) Structure	Multivariate Autoregressive (MAR) Structure
Resources share prices	**0.68**	**0.27**
Financials share prices	**0.67**	**0.42**
Industrial share prices	**0.75**	**0.26**
Price-earnings ratio	**0.30**	**0.28**
Price-dividend ratio	**0.36**	**0.28**

were very similar to those reported for the valuation ratios and the growth rates of the various measures of money under both the MIN and MAR structures. Complete details of these results are available upon request from the authors.

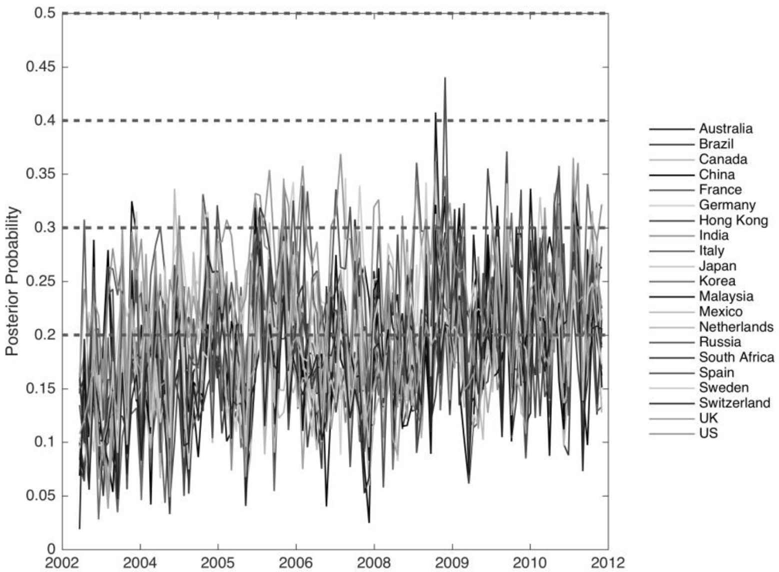
Hang-Seng	**0.25**	**0.97**
S&P 500	**0.31**	**0.33**
FTSE 100	**0.41**	**0.48**
CAC	**0.32**	**0.39**
NIKKEI	0.19	**0.69**
SSE	**0.25**	**0.30**
DAX	**0.32**	**0.41**
M1A	**0.20**	**0.32**
M1	0.18	**0.30**
M2	0.18	**0.34**
M3	**0.21**	**0.44**
Real effective exchange rate	**0.40**	**0.27**
Relative 90 days Treasury bill rate	**0.28**	**0.31**
Relative money market rate	**0.36**	**0.41**
Term spread	**0.20**	**0.60**
Manufacturing production growth rate	0.18	**0.38**
Employment growth rate	**0.23**	**0.40**
EPUs:		
Australia	**0.33**	**0.29**
Brazil	**0.20**	**0.38**
Canada	**0.29**	**0.26**
China	**0.32**	**0.46**
France	**0.22**	**0.41**
Germany	**0.25**	**0.27**
Hong Kong	**0.23**	**0.76**
India	0.14	**0.45**
Italy	0.18	**0.38**

Japan	0.17	**0.31**
South Korea	0.15	**0.38**
Malaysia	**0.22**	**0.35**
Mexico	**0.22**	**0.32**
The Netherlands	0.16	**0.68**
Russia	**0.27**	**0.31**
South Africa	**0.21**	**0.29**
Spain	**0.25**	**0.39**
Sweden	**0.20**	**0.28**
Switzerland	0.19	**0.31**
UK	**0.24**	**0.36**
US	**0.29**	**0.38**

Note: Bold red entries represent the selected edges for the MIN and MAR structures based on posterior probabilities greater than equal to 0.50; Bold green (blue) [brown] indicate posterior probabilities greater than equal to 0.40 (0.30) [0.20].

In order to gain further insight on the temporal evolution of the BGVAR and investigate whether structural (regime) shifts (as depicted in Aye *et al.*, (2013) and Balcilar *et al.*, (forthcoming) for South African stock returns) can reconcile the results with the previous study of Balcilar *et al.*, (forthcoming), we estimate the BGVAR in a rolling-window fashion. The rolling-window approach provides local estimates for the model parameters, and makes our linear BGVAR model adapt to the curvature of the relationship between the equity premium and the predictors, and hence, become somewhat comparable to the nonparametric approach of Balcilar *et al.*, (forthcoming), where one weighs the local estimates with unequal weights. The rolling window estimation uses an initial sample period of 1998:01-2002:12 and a 60-month rolling window estimation over the period of 2003:01-2012:03, i.e., a total of 111 rolling estimations. To be consistent with the full sample, the lag order of the VAR is set to 1, and 40,000 draws are used, with an initial burn-in of 10,000 from 50,000 draws to derive the posterior inclusion probabilities of the predictors.

Figure 1. Rolling Posterior Probabilities of the MIN Structure for EPU Indices



Note: Figure plots the rolling estimates of posterior probabilities of instantaneous relationship between the South African stock returns and EPU of 21 countries. Rolling estimation is performed with a fixed 60-month window size over the period of 2003:01-2012:03 with initial sample of 1998:01-2002:12. Dashed lines represent the threshold probabilities 0.20, 0.30, 0.40, and 0.50.

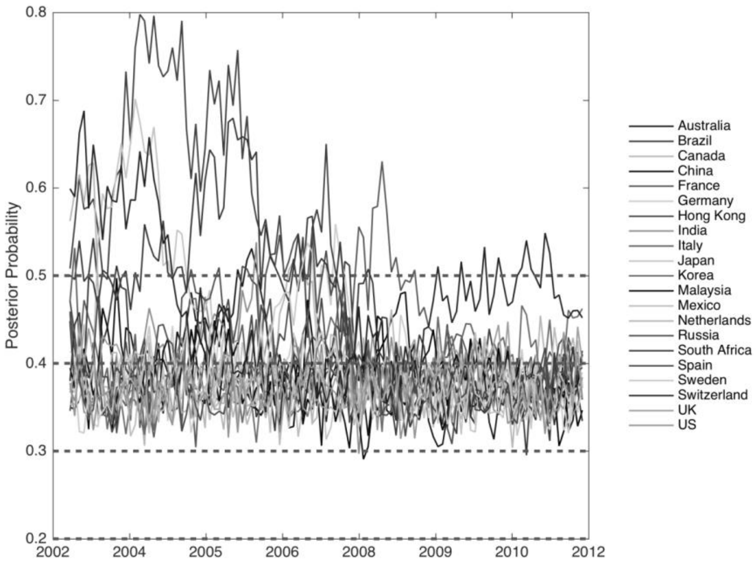
We first examine the rolling-window posterior probability estimates for instantaneous relationship between the equity premium and the EPUs, as plotted in Figure 1. Since, in this paper, we are primarily concerned with the ability of EPUs in predicting excess stock returns, we restrict the analysis to only the uncertainty measures.[12] Consistent with the full-sample estimates,

[12] The rolling-window posterior estimates of the various macroeconomic and financial predictors are available upon request from the authors. Table A1 in the Appendix however, presents the mean posterior probabilities for all the predictors under the rolling window

none of the instantaneous impact from EPU indices essentially exceeds the 0.50 threshold probability, except two spikes for Australia and Spain, which seem to be outliers. All the rolling estimates generally fall between 0.05 and 0.30 until 2005, and both the lower and upper bounds of this range shifts up by 0.05 after 2005. A similar pattern is also observed for the average of the posterior probabilities associated with the instantaneous relationships between EPU and the equity premium. The average is around 0.15 before 2005 and rise to 0.20 after 2006. Overall, the rolling estimates do not indicate any significant instantaneous impact from the EPU indices on South African stock returns.

estimation. As can be seen barring the stock returns of Hong Kong and Germany and the EPU of Hong Kong, no other predictors have lagged effects that exceed, on average, the 0.50 threshold under the MAR structure. But under the MIN structure, no predictors have on average rolling posterior probabilities that is greater than 0.50.

Figure 2. Rolling Posterior Probabilities of the MAR Structure for EPU Indices



Note: Figure plots the rolling estimates of posterior probabilities of lagged relationship between the South African stock returns and EPU of 21 countries. Also see Note to Figure 1.

Next in Figure 2, we display the rolling-window posterior probabilities of lagged impact from the EPU indices on the equity premium. Contrary to the probabilities of the instantaneous relationships, the lagged posterior probabilities show strong time-variation for several of the EPU indices in its relationship with the excess returns. Rolling posterior probabilities exceed the threshold of 0.50 in various sub-periods for 14 out of the 21 EPU series. The posterior probabilities strongly exceed the threshold 0.50 in prolonged periods particularly for Hong Kong, Japan, Russia, South Africa, and Switzerland. For Hong Kong, Japan, and South Africa, the probabilities are largely above the threshold of 0.50 before 2006; however, they mostly fall below this threshold after 2006. Lagged impact from EPUs of Russia and France exceed the 0.50 threshold between 2006 and 2009. For Switzerland, we observe an interesting pattern: the lagged EPU impact had high probabilities before 2005 and after 2009. Indeed, the posterior probability of Switzerland is the only one that exceeds 0.50 after 2009. Overall, the lagged impact from the EPUs of all the countries seem to have weakened after 2008, which corresponds to the post-subprime mortgage crisis period, and the associated global recession beginning in 2008. Interestingly, posterior probability estimates essentially are all above 0.30 for the entire period of 2003:01-2012:03. All of the lagged impact posterior probability estimates center around 0.38 consistently over the entire rolling-window estimation period. Compared to the instantaneous impact probability estimates in Figure 1, the lagged impact probability estimates are about 0.20 higher on average over the entire period of 2003:01-2012:03.

We summarize the rolling-window estimates in Table 2 with percentages of months out of total 111 rolling estimates for which the posterior probabilities are greater than the threshold probabilities of 0.20, 0.30, 0.40, and 0.50. For the instantaneous impact emanating from the EPU (Panel A of Table 2), the EPU inclusion probabilities never exceed the 0.50 threshold and the percentages are all 0.00%. The same holds for the 0.40 threshold, except for two exceptions where 0.90% of posterior probabilities exceed 0.40 for Australia and Spain. We observe small percentages at the 0.30 threshold except for US, for which the number of months where posterior probabilities exceed 0.30 is about 21%.

The percentages given in Panel B of Table 2 are for the lagged impact of the EPU indices. Percentage of months for which the posterior probabilities exceed the 0.20 and 0.30 thresholds are about 100% for all the EPU series. The percentages are moderate to high ranging from 9.01% (US) to 75.68% (Switzerland) for the 0.40 threshold. The percentage of months with posterior inclusion probabilities exceeding the 0.50 threshold is above zero for 14 out of 21 EPU series. For the 0.50 threshold, we observe no months with posterior probability above zero for China, South Korea, Malaysia, Mexico, Spain, UK, and US. The percentages under the 0.50 threshold are above 10% for Hong Kong (47.75%), South Africa (35.14%), Switzerland (27.93%), Japan (17.12%), and Russia (13.51%). Interestingly, rolling estimates do not show strong lagged predictability for the Netherlands for which only 5.41% of the rolling estimates have posterior probability exceeding 0.50. Thus, we observe significant lagged impact from most of the EPU series in various sub-periods. This result reconciles the findings of Balcilar *et al.*, (forthcoming) as they used a method capable of finding impact at various quantiles of the conditional distribution of the returns. Their approach is most likely to capture the significant impact the rolling estimates indicate in various sub-periods.

Table 2. Percentage of Months with Posterior Probability Greater than the Threshold Probability for the EPU Variables

Threshold probability:	0.20	0.30	0.40	0.50
	Panel A: Multivariate Instantaneous (MIN) Structure			
Australia	37.84%	9.91%	0.90%	0.00%
Brazil	29.73%	0.90%	0.00%	0.00%
Canada	46.85%	3.60%	0.00%	0.00%
China	51.35%	5.41%	0.00%	0.00%
France	67.57%	7.21%	0.00%	0.00%
Germany	63.06%	9.91%	0.00%	0.00%
Hong Kong	26.13%	1.80%	0.00%	0.00%
India	39.64%	8.11%	0.00%	0.00%
Italy	34.23%	2.70%	0.00%	0.00%
Japan	48.65%	2.70%	0.00%	0.00%
South Korea	41.44%	3.60%	0.00%	0.00%
Malaysia	33.33%	0.90%	0.00%	0.00%
Mexico	34.23%	1.80%	0.00%	0.00%
The Netherlands	31.53%	0.90%	0.00%	0.00%
Russia	59.46%	9.01%	0.00%	0.00%
South Africa	43.24%	4.50%	0.00%	0.00%
Spain	42.34%	6.31%	0.90%	0.00%
Sweden	41.44%	1.80%	0.00%	0.00%
Switzerland	34.23%	2.70%	0.00%	0.00%
UK	40.54%	5.41%	0.00%	0.00%
US	81.08%	20.72%	0.00%	0.00%

	Panel B: Multivariate Autoregressive (MAR) Structure			
Australia	100.00 %	100.00%	34.23%	3.60%
Brazil	100.00 %	99.10%	34.23%	6.31%
Canada	100.00 %	100.00%	25.23%	2.70%
China	100.00 %	100.00%	21.62%	0.00%
France	100.00 %	100.00%	39.64%	8.11%
Germany	100.00 %	100.00%	27.93%	3.60%
Hong Kong	100.00 %	100.00%	66.67%	47.75%
India	100.00 %	99.10%	27.03%	0.90%
Italy	100.00 %	100.00%	40.54%	0.90%
Japan	100.00 %	100.00%	30.63%	17.12%
South Korea	100.00 %	100.00%	37.84%	0.00%
Malaysia	100.00 %	99.10%	34.23%	0.00%
Mexico	100.00 %	100.00%	21.62%	0.00%
The Netherlands	100.00 %	100.00%	18.92%	5.41%
Russia	100.00 %	100.00%	46.85%	13.51%
South Africa	100.00 %	100.00%	63.06%	35.14%
Spain	100.00 %	100.00%	26.13%	0.00%
Sweden	100.00 %	100.00%	31.53%	2.70%

Switzerland	100.00 %	100.00%	75.68%	27.93%
UK	100.00 %	100.00%	25.23%	0.00%
US	100.00 %	100.00%	9.01%	0.00%

Note: Table reports the percentage of months the rolling posterior inclusion probabilities exceed the threshold probability. Rolling estimation is performed with a fixed 60-month window size over the period of 2003:01-2012:03 with the initial estimation period of 1998:01-2002:12. Panel A reports results for the instantaneous (MIN) structure, while Panel B reports the results for the lagged (MAR) structure. Threshold probabilities are 0.20, 0.30, 0.40, and 0.50.

4 – Conclusion

A recent and growing international literature show that stock returns can be predicted using news-based measures of economic policy uncertainty (EPU). In this regard, a recent study by Balcilar *et al.*, (forthcoming) for South Africa shows the same to hold true based on an in-sample bivariate causality-in-quantiles approach. In this paper, we revisit this result using a Bayesian graphical model with full sample estimates over the period of 1998:01-2012:01 and rolling-window estimates over the period of 2003:01-2012:03 (using an initial estimation sample period of 1998:01-2002:12), which allows us to incorporate as many as 43 predictors simultaneously, including the 21 EPUs considered by Balcilar *et al.*, (forthcoming). The Bayesian approach also allows us to analyse instantaneous relationships besides the lagged relationships between the South African excess stock returns and the various predictors. Rolling-window estimation helps us to control for structural breaks and investigate the temporal variation in the predictability. As far as instantaneous relationship goes, none of the 21 EPUs are found to be important based on the full-sample or, i.e., have a posterior probability that is greater than 0.50. It is only the sectoral (industrial, financial and resources) stock returns of South Africa that satisfies this criterion. The results for the EPUs obtained under the full-sample estimation, are found to carry over to the rolling estimation as well. When we look at lagged relationships, though all the 21 EPUs have posterior probabilities in excess of 0.20, it is only in the case of Hong Kong and the Netherlands, where the probability of inclusion exceeds 0.50 in the full sample estimates. The other variables that fall within this category are the term-spread, and the stock returns of Hong Kong and Japan. The rolling estimates for the lagged impact however, indicate predictability for 14 EPUs, where the posterior probabilities exceed 0.50 in various sub-periods. More than 10% of the rolling posterior inclusion probabilities exceed 0.50 for Hong Kong (47.75%), South Africa (35.14%), Switzerland (27.93%), Japan (17.12%), and Russia (13.51%). Moreover, the rolling estimates show significant time-variation with weaker predictability observed in the post-2008 period. Our results highlight the importance of modelling simultaneously many indicators and also analysing predictability in a time-varying fashion rather than a fixed full sample period.

Our results have important implications for both policymakers and portfolio managers. It is obvious from our results that economic uncertainty does affect the South African stock market, though not necessarily all the time, but surely when uncertainty is relatively high. With South Africa being a small open economy, the impact of global uncertainty on capital flows and hence, the equity market is unavoidable and impossible to control, unless stringent regulations are placed on the capital account. However, this should not be an optimal policy choice for an emerging market economy like South Africa, which relies heavily on foreign investment. However, what the policymakers in South Africa, should aim to avoid is the domestic uncertainty in economic policy making. Given that this is under their control, uncertainty in domestic policy making should be avoided at all cost to negatively impact the confidence of domestic and foreign investors. The policymakers need to send out clear signals in terms of policies to avoid creating any confusion, and hence, uncertainty, in the equity market. For portfolio managers, looking to carry out optimal asset allocation; an important message is that, using constant parameter models can be highly misleading. This is because, with constant parameter models, it does seem that the South African stock market is efficient in the sense that, it remains highly unaffected by its predictors, barring few foreign stock markets. However, as we show, when we use a time-varying approach, there are many predictors, especially uncertainty related variables which becomes important in predicting the South African stock returns. In other words, portfolio managers should conduct time-varying analysis of their models for asset allocation, as different predictors carry different importance at various points in time. Relying on an average-based (constant-parameter) approach, could lead to sub-optimal allocation of portfolios, given that time-varying information content of several predictors might not end up being captured. As part of future research, it would be interesting to revisit our analysis using nonparametric Bayesian quantile regressions that allows us to consider all the predictors simultaneously, and in the process also forecast out-of-sample, since in-sample predictability does not guarantee the same for the out-of-sample (Rapach and Zhou, 2013).

In addition, given that we are dealing with a variable measuring economic uncertainty, it would also be worthwhile to analyse the impact on the volatility of the South African stock market. Note that, appropriate modeling and prediction of volatility is of importance due to several reasons for portfolio managers and policy makers: Firstly, when volatility is interpreted as uncertainty, it becomes a key input to investment decisions and portfolio choices. Secondly, volatility is the most important variable in the pricing of derivative securities. To price an option, one needs reliable estimates of the volatility of the underlying assets. Thirdly, financial risk management according to the Basle Accord as established in 1996 also requires modeling and forecasting of volatility as a compulsory input to risk-management for financial institutions around the world. Evidently, appropriate modeling and accurate prediction of the process of volatility has ample implications for portfolio selection, the pricing of derivative securities and risk management. Thus, it is of paramount importance, that we analyze the role played by economic uncertainty in affecting volatility of stock returns in South Africa. It is a likely possibility that uncertainty affects volatility of equity markets relatively more than its returns, but this remains to be tested.

Appendix:

Table A1. Rolling Mean Average Posterior Probabilities of Predictors:

Variables	Multivariate Instantaneous (MIN) Structure	Multivariate Autoregressive (MAR) Structure
Resources share prices	0.43	0.43
Financials share prices	0.30	0.38
Industrial share prices	0.48	0.39
Price-earnings ratio	0.28	0.41
Price-dividend ratio	0.23	0.38
Hang-Seng	0.19	**0.59**
S&P 500	0.29	0.39
FTSE 100	0.35	0.45
CAC	0.31	0.39
NIKKEI	0.19	0.40
SSE	0.32	0.38
DAX	0.19	**0.50**
M1A	0.18	0.36
M1	0.19	0.36
M2	0.19	0.42
M3	0.20	0.40
Real effective exchange rate	0.23	0.40
Relative 90 days Treasury bill rate	0.26	0.45
Relative money market rate	0.27	0.45
Term spread	0.24	0.42
Manufacturing production growth rate	0.17	0.38

Employment growth rate	0.17	0.47
EPUs:		
Australia	0.19	0.39
Brazil	0.17	0.39
Canada	0.19	0.38
China	0.20	0.38
France	0.23	0.40
Germany	0.21	0.39
Hong Kong	0.16	**0.51**
India	0.19	0.39
Italy	0.18	0.40
Japan	0.20	0.41
South Korea	0.19	0.39
Malaysia	0.17	0.39
Mexico	0.18	0.38
The Netherlands	0.17	0.38
Russia	0.21	0.41
South Africa	0.19	0.46
Spain	0.19	0.39
Sweden	0.19	0.39
Switzerland	0.17	0.47
UK	0.19	0.38
US	0.25	0.37

Note: Bold red entries represent the selected edges for the MIN and MAR structures based on posterior probabilities greater than equal to 0.50. Rolling estimation is performed with a fixed 60-month window size over the period of 2003:01-2012:03 with the initial estimation period of 1998:01-2002:12.

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