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2015

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Previous Version: December 2015
This Version: January 2016

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Abstract

We assess the robust macro determinants of the real exchange rate in Mauritius under model uncertainty by utilizing Bayesian Model Averaging (BMA). We introduce a broader range of potential macro determinants of the real exchange rate in Mauritius. Then we tackle the issue of model uncertainty when identifying these macro determinants of the real exchange rate by exploring the impact of different priors on the model size, and different priors on model coefficients on the posterior estimates. We identify the real money supply, and the real productivity to be the robust macro determinants of the real exchange rate in Mauritius. Their coefficient signs are also theoretically consistent. The real money supply impact on the real exchange rate negatively, whereas the real productivity impact on it positively. Our results remain robust to different priors on the model size, and to different priors on model coefficients.

Keywords: Model Uncertainty, Bayesian Model Averaging (BMA), Macro Determinants, Real Exchange Rate, Mauritius

JEL Codes: C11, C15, F31

1. Introduction

This paper explores the macro determinants of the real exchange rate in Mauritius for the period 1976-2012. A bulk of studies, today, has focused on identifying the fundamental drivers of the real exchange rate.[2] This is understandable because the real exchange rate, which, to a very large extent, dictates trade flows and international competiveness, may lose its value if it determinants are not known (see Kia, 2013). On this premise, understanding the macro-economic determinants of the real exchange rate is, therefore, very important for monetary policymakers, since the influence of the real exchange rate on the real economy can only be sufficiently assessed if the sources of shocks that drive it are known (see Detken *et al.*, 2002).

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2 A survey of earlier papers can be found in MacDonald (1995), Rogoff (1996), and Hinkle and Montiel (1999). For a very recent survey, see Lee *et al.* (2008).

In the literature, the issue that resurfaces frequently is the approach used to estimate the links between the real exchange rate and its macro determinants. For example, under the purchasing power parity (PPP) approach, the long-run real exchange rate is assumed to be stationary so that any deviation from this rate reflects misalignment. Thus, the determinants of the real exchange rate are the shocks that drive it from the equilibrium rate. This notion has, however, been heavily criticized due to the slow mean-reverting property of the real exchange rate (see MacDonald and Ricci, 2003). The Behavioural Equilibrium Exchange Rate (BEER) approach as introduced by Clark and MacDonald (1999) contends, instead, that the real exchange rate and its determinants should be viewed as I(1) processes. This means that cointegration analysis can be utilized to assess the influence of the determinants on the real exchange rate (see Elbadawi and Soto, 1994; Edwards, 1994; Cardenas, 1997; Montiel, 1997; Loayza and Lopez, 1997; Aron *et al.*, 2000; MacDonald and Ricci, 2003; Iman and Minoiu, 2011). Some researchers prefer to setup and simulate a dynamic general equilibrium macroeconomic model using parametric calibration and data suitable for a given country (see Clark *et al.*, 1994; Williamson, 1994; Stein *et al.*, 1995). Other researchers utilize single equation models and partial equilibrium models to examine the movement of the real exchange rate in the long run (see Driver and Wren-Lewis, 1997; Ghei and Pritchett, 1999).

The current paper brings some new contributions into the literature. First, when compared to the existing studies, the paper utilizes a much broader range of potential macro determinants (i.e. 21 potential macro determinants) of the real exchange rate for a small open economy, Mauritius. To the best of our knowledge, this is the first paper to do so. Second, the paper tackles the issue of model uncertainty when identifying these macro determinants of the real exchange rate. The paper does this by exploring the impact of different priors on the model size, and different priors on model coefficients on the posterior estimates. When the BMA approach is utilized this way, the paper avoids unintended consequences of eliciting inappropriate priors, and dealing sufficiently with multicollinearity issues.

The remaining sections of this paper are structured as follows. Section 2 briefly explores the exchange rate history of Mauritius. Section 3 presents a simple model of the real exchange rate. Section 4 presents the model specification and the prior structures of the BMA approach. Section 5 presents the empirical results. Section 6 concludes the paper.

2. A Brief History of the Exchange Rate Policy of Mauritius

Mauritius has practiced fairly mixed exchange rate regimes from independence to date. Prior to independence in 1968, the country shifted from a currency board system to a pegged system in November 1967. The Mauritian currency, the rupee, was pegged to the

British pound (see IMF, 2008; Imam and Minoiu, 2011). Under this pegged system, the country employed a dual exchange market. All capital account transactions were separated from current account transactions. To this end, all capital transfers attracted a stamp duty of 15% under the pegged system (see Imam and Minoiu, 2011).

In June 1972, Mauritius created a central exchange rate with Special Drawing Rights (SDRs), following the weakening of the British pound in 1971. However, the second exchange rate for capital transfers remained in place. The rupee was officially pegged to the SDR in January 1976 around a bandwidth of 2%. This was the case in theory but the rate was actually a crawling band around the US dollar (see Imam and Minoiu, 2011). Between 1976 and 1978, the rupee was considered overvalued. Thus, the Bank of Mauritius undertook devaluation exercises in 1979 and 1981. That apart, the stamp duty was increased from 36% to 45% for capital transfers in July 1981 (see IMF, 2008).

In June 1982, the Bank of Mauritius again intervened in the foreign market by delinking the rupee from the SDR. The rupee was then pegged to a trade-weighted basket of currencies of the country's major trade partners under an IMF liberalization initiative. In spite of these changes, the exchange rate remained pegged *de facto* to the US dollar with a bandwidth of 5% (see Broda, 2002; Reinhard and Rogoff, 2004). There was a limit specified on the sale of foreign currency for travelling purposes as a form of capital control. The monetary authorities maintained a multiple currency from this period till the mid-1990s. As part of the multiple currency policy, a tax of 15% was charged on some capital remittances. This tax remained in operation till 1992 when all forms of exchange rate restrictions were eliminated. The *de facto* crawling bandwidth was reduced from 5% to 2% in 1992. Foreign currency transactions were fully liberalized in July 1994. The country adopted a managed float exchange rate regime from this period onwards. The Bank of Mauritius occasionally intervenes in the foreign exchange market to minimize exchange rate volatilities.

3. A Simple Theoretical Model of the Real Exchange Rate

Although various authors have successfully formulated formal models of the real exchange rate, which incorporates its determinants (see, e.g., Mundell, 1961; McKinnon, 1963; Ostry, 1988; Khan and Ostry, 1991; Faruqee, 1995; Frankel, 1995; Montiel, 1999; Kia, 2013), this paper draws on the model formulated by Edwards (1993) largely due to its empirical appeal. This is a simple model of the real exchange rate in which there is simultaneous equilibrium of the current account balance and the tradable good market (see Drine and Rault, 2015).

The basic building blocks of the model entail the following. Suppose there is a small

open economy with three sectors, which produces three goods. The sectors are export, import, non-tradable. These sectors produce, respectively, exports (X), imports (M), and non-tradables (N). Suppose that the economy is populated by consumers of the imports and the non-tradables. The economy practices a floating exchange rate regime, so that its floating nominal exchange rate in all transactions is denoted E.

In addition to the above assumptions, suppose that P_X, P_M and P_N are the prices of exports, imports and non-tradables, respectively. By taking the world price of exports as the numeraire (i.e. $P_X^* = 1$), it holds that the domestic price of exports will be $P_X = EP_X^* = E$. This relation holds directly from the absolute form of the purchasing power parity (PPP) hypothesis. Denote the world price of imports as P_M^*. It is straightforward to define the domestic relative prices of exports (e_X) and imports (e_X) to non-tradables as E/P_N and P_M/P_N, respectively. Thus, the relative price of imports to non-tradables can be formulated as (see Drine and Rault, 2015)

$$e_M^* = EP_M^*/P_N \tag{3.1}$$

Suppose the economy imposes tariffs on imports. Then the price of imports will be

$$P_M = EP_M^* + \eta, \quad \eta = tariff\ rate \tag{3.2}$$

Let the total output (Q) in this small open economy be given by the following equation

$$Q = Q_X(e_X) + Q_N(e_X), \ Q_X' > 0 \text{ and } Q_N' < 0 \tag{3.3}$$

Similarly, let private consumption (C) in the economy be defined by the following

$$C = C_M(e_M) + C_N(e_M), \ C_M' < 0 \text{ and } C_N' > 0 \tag{3.4}$$

where C_M and C_N denote, respectively, consumption on imports and non-tradables.

A few more equations will close the model. In the spirit of Cassel (1918), define the real exchange rate (e) for this economy as the relative price of tradables to non-tradables. That is

$$e = \rho e_M + (1-\rho)e_X = E(\rho P_M^* + (1-\rho)) + \rho\eta/P_N, \rho \in (0,1) \tag{3.5}$$

Now, suppose that capital in this economy is perfectly mobile, and denote net foreign assets of the economy by A. Suppose also that this economy invests its net foreign assets at the international real interest rate r^*. Then, the economy's current account (CA) in any given year will be the sum of its net interest earnings on A and its trade surplus (i.e. $X - M$). This is given by the following expression (see Drine and Rault, 2015)

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$$CA = r^*A + Q_X\,(e_X) - P_M^*C_M(e_M) \tag{3.6}$$

In addition, define a change in the foreign currency reserves (R) in the economy as

$$R = CA + KI \tag{3.7}$$

where KI denotes net capital inflows. Assume that in the short and the intermediate period the economy may lose or gain foreign currency reserves. Then it follows that the current account of this economy is sustainable if the current account deficit plus the net capital inflows in the long run sum up to zero. This holds that the official reserves of the economy do not change. Thus, the economy is in an external equilibrium if the sum of the current account balance and the capital account balance equal to zero. This can be expressed as follows (see Edwards, 1993)

$$r^*A + Q_X\,(e_X) - P_M^*C_M(e_M) + KI = 0 \tag{3.8}$$

$$C_N(e_M) + G_N = Q_N(e_X) \tag{3.9}$$

where G_N is public spending on non-tradables. Thereby, the equilibrium real exchange rate is the rate, which ensures, simultaneously, external and internal equilibrium. Thus, using *Eqs.* (3.8) and (3.9), we can formulate the equilibrium real exchange rate (e^*) as a function of η, r^*, P_M^*, A, KI, and G_N (see Drine and Rault, 2015). That is

$$e^* = e^*(\eta, r^*, P_M^*, A, KI, G_N) \tag{3.10}$$

To reiterate, the equilibrium real exchange rate depends on the trade policy (i.e. trade openness), foreign interest rate, terms of trade[3], foreign capital flows[4], and public spending[5]. In principle, these are the most often identified determinants of the real exchange rate in the long run (see Elbadawi and Soto, 1994; Cardenas, 1997; Loayza and Lopez, 1997; Montiel, 1999; Aron *et al.*, 2000; MacDonald and Ricci, 2003; Iman and Minoiu, 2011; Drine and Rault, 2015).

Other variables such as the world commodity prices (see Cashin *et al.*, 2002; Chen and Rogoff, 2002; MacDonald, 2002; MacDonald and Ricci, 2003), real money supply (see Kia, 2013), real productivity (see Detken *et al.*, 2002; Kia, 2013; Drine and Rault, 2015), and foreign direct investment (see Drine and Rault, 2015) have also been identified in the literature as macroeconomic determinants of the real exchange rate. These variables are utilized in our paper.

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[3] See Montiel (1997), Goldfajn and Valdes (1999), and Imam and Minoiu (2011).
[4] See Lane and Milesti-Ferretti (2000), MacDonald and Ricci (2003), Imam and Minoiu (2011).
[5] See De Gregorio *et al.* (1994), Montiel (1997), MacDonald and Ricci (2003), and Imam and Minoiu (2011).

On the empirical front, different approaches have been utilized to estimate the functional relationship in *Eq.* (3.10). Each approach has its advantages and drawbacks. In this paper, we utilized the Bayesian Model Averaging (BMA) to estimate this function. We discuss this approach in the next section.

4. Model Specification and Prior Structures

In this paper, we analyze the core macro determinants of the real exchange in Mauritius using BMA. This approach is very useful in the sense that it addresses model uncertainty in a canonical regression specification (see Hoeting *et al.*, 1999). To make this point clear, let us assume that our model is a linear regression of the following form

$$y = \alpha_\gamma + X_\gamma \beta_\gamma + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 I) \quad (4.1)$$

where y is the dependent variable (i.e. the real exchange rate), α_γ and β_γ denote the intercept and the coefficient terms, respectively, X_γ is a matrix of explanatory variables (i.e. the macro determinants of the real exchange rate), ε is an IID error term whose variance is σ^2.

Question: Which variables should enter into the matrix X_γ, among a host of potential explanatory variables? This is a problem because we have a universe of explanatory variables X that may explain the variation in y. In principle, the choice of $X_\gamma \in \{X\}$ to be included in the model must be based on their relative importance. In the canonical linear regression problem, a single model contains all the explanatory variables, rendering the approach inefficient or even infeasible with a limited number of observations (see Chipman *et al.*, 2001).

The BMA approach emends this model uncertainty problem by estimating models for all possible combinations of $\{X\}$ and constructing a weighted average over all of them (see Feldkircher and Zeugner, 2015). Supposing that X contains K potential variables, the BMA approach entails that we estimate 2^K models, which is represented by the model candidate space $M = \{M_1, M_2, \dots, M_{2^K}\}$. Bayes theorem provides the useful guide for obtaining model weights, which are estimated from the posterior model probabilities. Using the Bayes theorem, we have that

$$p(M_\gamma | y, X) = \frac{p(y | M_\gamma, X) p(M_\gamma)}{p(y | X)} = \frac{p(y | M_\gamma, X) p(M_\gamma)}{\sum_{s=1}^{2^K} p(y | M_s, X) p(M_s)} \quad (4.2)$$

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where $p(y|X)$ is the integrated likelihood which is constant over all models and it is thus simply a multiplicative term. Hence, the posterior model probability (PMP) is proportional to the integrated likelihood $p(y|M_\gamma, X)$, which reflects the probability of the data given model M_γ.

The term $p(y|M_\gamma, X)p(M_\gamma)$, the product of the marginal likelihood of model M_γ and the prior model probability $p(M_\gamma)$, shows how the researcher believes model M_γ is probable prior to observing the data. $p(y|X)$ and $p(y|M_\gamma, X)$ are different in the sense that integration is done over the model space $p(y|X)$ but for a given model over the parameter space $p(y|M_\gamma, X)$. We can infer the posterior model probabilities (PMPs) and the model weighted posterior distribution for any statistic θ (e.g., the estimator of the coefficient β_γ), by renormalization *Eq.* (4.2) such that

$$p(\theta|y, X) = \sum_{\gamma=1}^{2^K} p(y|M_\gamma, y, X) \frac{p(M_\gamma|X, y)p(M_\gamma)}{\sum_{s=1}^{2^K} p(M_s|y, X)p(M_s)} \qquad (4.3)$$

Eq. (4.3) is very crucial because all relevant posterior computations are based on it. For example, we can compute the posterior moments of the coefficient vector β_γ, which is a weighted average over all models. In a similar fashion, we can also compute the posterior inclusion probabilities (PIPs), which can be used to evaluate the importance of each explanatory variable (i.e. the macro determinants) in the model. This is computed as the sum of probabilities for all models in which the covariate is included (see Feldkircher and Zeugner, 2015).

In practice, the elicitation of the model prior $p(M_\gamma)$ reflects the prior believes of the researcher. A wide range of model priors exists in the literature. As argued by Crespo Cuaresma *et al.*, (2014), majority of the studies have utilized diffuse priors, thereby assigning equal probability to all possible models. This translates to imposing a mean prior model size of $K/2$. Contrary to these studies, other studies have assigned more prior weight to relatively pragmatic models by assuming Bernoulli distributions with fixed parameter π on the inclusion probability for each variable and using the expected model size, πK, to elicit the prior (see Sala-i-Martin *et al.*, 2004). Nevertheless, the recent literature has advanced the elicitation of Binomial-Beta prior distribution. Ley and Steel (2009) argued in favour of this prior, using the original ideas presented in Brown *et al.* (1998). Essentially, this prior elicitation strategy imposes a Beta hyperprior distribution on π, which happens to be the parameter of the Bernoulli distribution for the inclusion of each explanatory variable in the model. Ley and Steel (2009) argued that this prior elicitation strategy is powerful because it admits very different prior structures on the model size (see Crespo Cuaresma *et al.*, 2014). In this paper, we utilize the Binomial-

Beta prior and compare it performance against other competing priors.

In the BMA literature, the reliability of the regression coefficients depends heavily on the prior structure imposed by the researcher. Practically all Bayesian linear models build on the Zellner's (1986) g prior structure. The value of the Zellner's g prior corresponds to the degree of prior uncertainty (see Feldkircher and Zeugner, 2015). Majority of the studies in the literature have favoured the imposition of a fixed g prior. For example, Fernández *et al*. (2001) have argued for a comparatively large g prior to minimize prior impact on the results, stay close to the OLS coefficients, and represent the absolute lack of prior knowledge. In contrast, Ciccone and Jarociński (2010) have shown that a large g can be non-robust to noise innovations, thereby exposing the model to over-fitting problems. Eicher *et al.* (2011) favoured the choice of intermediate fixed values for the g priors, whereas Liang *et al.* (2008) argued for default specifications (see Feldkircher and Zeugner, 2015).

The fixed g prior approach has, however, been heavily criticized to be very vulnerable to unintended consequences. Indeed, Feldkircher (2012) argued that under a large g (i.e. when the shrinkage factor is near unity), the posterior estimates could be over-fitted. Under this condition, the coefficients are poorly estimated, whilst the posterior model probabilities (PMPs) are concentrated. Model sizes become smaller, leading to skewed PIP distribution (see Feldkircher, 2012). In contrast to this, when the g prior is low, the data signals will not be sufficiently exploited, thereby leading to very similar intermediate PIPs for a large share of covariates (see Feldkircher, 2012). To emend this problem, the recent literature has argued for flexible g priors. Liang *et al.* (2008) have provided an excellent survey of these studies. Following the lead of Liang *et al.* (2008), we imposed a hyperprior on g. We set the expected prior value of the shrinkage factor to the Uniform Information Prior (UIP) and compare its PIPs to other competing flexible g priors.

We sample the posterior distributions of interest over the model space using the birth/death Markov Chain Monte Carlo Model Composite (MC^3) sampler[6]. The sampler is the commonly utilized in the BMA literature. The sampling is done such that one of the covariates is randomly selected at a time. Given that the covariate selected is already included in the present model, say M_i, it holds that the candidate model, say M_j will contain the same set of covariates as M_i except that the selected covariate will be discarded. Given that the covariate selected is not in M_i, then the candidate model will contain all the covariates from M_i in addition to the selected covariate (see Feldkircher and Zeugner, 2015).

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[6] Refer to Stephens (2000), and LeSage and Parent (2007) for excellent description of this sampler. See also the Technical Appendix.

5. The Empirical Results

The dataset is annual and contains 22 macroeconomic variables over the period 1976-2012. The definition and source of each of these variables are in the Data Appendix. Where the original data is measured in current terms, we adjusted it to constant terms using national price data. The variables are in two categories. The first category consists of the frequently identified macro determinants of the real exchange rate in the literature. These include, among others, trade openness, foreign interest rate, terms of trade, world commodity prices, net foreign assets, and public spending. The second category consists of other variables, which may influence the real exchange rate but are largely overlooked in the literature. These variables are, among others, average interest on new external debt commitments, debt service on external debt, real domestic investment, domestic inflation, real net official development assistance and official aid received, and the growth of the world economy. All the variables are demeaned to invoke stationarity.

The empirical results are presented in threefold. In the first, we evaluate the macro determinants of the real exchange rate using our baseline specification. This specification uses the Binomial-Beta distribution (as in Liang *et al.*, 2008, and Feldkircher, 2012; Crespo Cuaresma *et al.*, 2014) on the model prior, and imposes a hyperprior on g with the expected prior value of the shrinkage factor restricted to the UIP. In all cases, except in the case of the tessellation prior, we sampled the posterior distributions of interest over the model space using the birth/death MC^3 sampler. In the second, we evaluate the robustness of these macro determinants to alternative elicitation of flexible Zellner's g priors. Here, we compare the PIPs of g=UIP to competing flexible g priors such as g=RIC[7], g=BRIC[8], and g=EBL[9]. Finally, we recognize that under this setting, the inclusion of several macro determinants can pose multicollinearity problems. Hence, we controlled for multicollinearity in the macro determinants using three competing model priors namely: the tessellation prior (see George, 2010), the weak heredity prior (see Chipman, 1996), and the general dilution prior (see Chipman, 1996). In the tessellation prior case, we utilize the MC^3 tessellation sampler proposed in George (2010). We maintain the flexible hyperprior g=UIP for these competing model priors, and compare their PIPs with the benchmark model.

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[7] RIC denotes the risk inflation criterion proposed by Foster and George (1994), whereby the hyperprior on g is set to K^2. K denotes the total number of covariates in the model.

[8] BRIC denotes the benchmark risk inflation prior proposed by Fernández *et al.* (2001), whereby the hyperprior on g is set to $max(N, K^2)$. N is the total number of observations.

[9] EBL denotes the local empirical Bayes prior advocated by George and Foster (2000), and Hansen and Yu (2001), whereby the hyperprior on g is set to $g_\gamma = argmax_g \ p(y|M_\gamma, X, g)$. Here, the information contained in the data (y, X) is used to elicit g via maximum likelihood.

5.1 Macro Determinants of the Real Exchange Rate

Table 2 shows the results stemming from our benchmark specification of the model prior structure, and the results based on alternative specifications of the flexible Zellner's g prior on the regression coefficients. Each of the columns in Table 2 reports, respectively, the posterior inclusion probabilities (PIPs) of each macro-determinant of the real exchange rate, the posterior mean (PM), and the posterior standard deviation (PSD) of the posterior distribution for the associated parameter. These results are based on 6,000,000 draws of the MC^3 sampler, 3,000,000 burn-in iterations, and a Binomial-Beta prior for the model size expected to be K/2 explanatory variables. As a rule of thumb, the importance of the macro determinants in the model can be interpreted in terms of their PIPs as follows: 50-75% PIP is weak, 75-95% PIP is substantial, 95-99% PIP is strong, and 99%+ PIP is decisive (see Kass and Raftery, 1995; Eicher *et al.*, 2009; Crespo Cuaresma *et al.*, 2014). Hence, an explanatory variable whose PIP is greater than the threshold of 0.5 is adjudged as robust (see Crespo Cuaresma *et al.*, 2014).

The second column in Table 2 reports the results for the benchmark model, which is based on 21 macro determinants of the real exchange rate (see Data Appendix for details). The real money supply and the real productivity, as proxy by LNRMS and LNRGDP, respectively, are identified as the robust macro determinants of the real exchange rate in Mauritius. The coefficients of these robust macro determinants have the expected signs (see Figure 4). The real money supply impact on the real exchange rate negatively, which is consistent with the theory. Higher real money supply stimulates increases in the domestic price level, which in turn lowers the real exchange rate in the long run (see Kia, 2013). The real productivity, in contrast, impact on the real exchange rate positively. Increasing real productivity enhances the earning capacity of the labour force. This is translated into higher real demand for money, which lowers domestic price level, thereby leading to higher real exchange rate (see Kia, 2013). However, whereas the posterior standard deviation is relatively small for the real money supply, it has been moderately high for the real productivity. Therefore, the real money supply appears to be the more reliable macro determinant of the real exchange rate in Mauritius than the real productivity.

Figure 1 displays the marginal posterior densities for the coefficients of the robust macro determinants of the real exchange rate based on 5000 models (i.e. coefficients with the largest PIPs). The upper panel of Figure 1 shows the posterior distribution of the coefficient of the real money supply. This distribution is very concentrated around the posterior mean of -0.477 with a PIP of 99.95%. Similarly, the lower panel of Figure 1 shows the posterior distribution of the coefficient of the real productivity. This distribution is also very concentrated around the posterior mean of 0.748 with a PIP of

97%. These marginal posterior densities clearly show that the real money supply and the real productivity explain the real exchange rate in Mauritius.

5.2 Robustness of the Results to Alternative Elicitation of Zellner's g Priors

As argued earlier (see Section 4), the choice of the prior structure on the regression coefficients can have massive influence on the posterior estimates. This issue has generated considerable discussion in the BMA literature (see Liang *et al.*, 2008; Ciccone and Jarociński, 2010; Eicher *et al.*, 2011; Feldkircher, 2012). Recent studies have argued for the use of hyper-g prior structure to avoid unintended posterior consequences (see Liang *et al.*, 2008; Feldkircher, 2012). In this section, we evaluate the robustness of these macro determinants to alternative elicitation of hyper-g priors. Specifically, we compare the PIPs of g=UIP to competing hyper-g priors such as g=RIC, g=BRIC, and g=EBL. The third, fourth, and fifth columns of Table 2 report the PIPs, PMs, and PSDs of these different elicitation of Zellner's g prior. The posterior estimates of these different hyper-g priors are remarkably similar to the benchmark specification (i.e. g=UIP) in column two of Table 2. A better way to appreciate the similarity is by looking at Figure 2, which shows the posterior inclusion probabilities (PIPs) and the standardized coefficients based on the four different flexible Zellner's g prior structures. The upper panel plots the PIPs, whereas the lower panel plots the standardized coefficients. By carefully observing Figure 2, we can see that the earlier results remain robust to different flexible Zellner's g prior structures (albeit, the PIPs based on the g=EBL diverged minimally). Therefore, the real money supply and the real productivity remain the robust macro determinants of the real exchange rate in Mauritius.

5.3 Controlling for Multicollinearity in the Macro Determinants

In this section, we tackle a critical issue, which can render the results inefficient – multicollinearity. We have estimated a model, which contains several explanatory variables. In principle, these macroeconomic variables are related in one way or the other. This means that we cannot take multicollinearity for granted. Some authors have devoted much attention to dealing with this problem in the Bayesian literature (see Chipman, 1996; George, 2010). To assess the robustness of the macro determinants to multicollinearity, we employ three priors on the model size, namely: (i) the weak heredity prior (see Chipman, 1996); (ii) the general dilution prior (see Chipman, 1996); and (iii) the tessellation prior (see George, 2010). In the case of the tessellation prior, we utilize the MCMC tessellation sampler proposed in George (2010). We maintain the flexible hyperprior g=UIP for these competing model priors, and compare their PIPs with the benchmark model. In all cases, the estimated results are based on 6,000,000 draws and

3,000,000 burn-in iterations. These results are reported in Table 3. Clearly, the estimated results for the robust macro determinants are very similar, except in the case of the weak heredity prior where the posterior coefficients are slightly overestimated. The evidence is even clearer if we carefully observe Figure 3, which displays the posterior inclusion probabilities (PIPs) and the standardized coefficients based on the four different specifications of model prior structure for the model size. The upper panel shows the PIPs, whereas the lower panel shows the standardized coefficients. That the posterior results based on the weak heredity prior diverged from the rest is to be expected because this prior deals better with multicollinearity introduced by interaction terms (see Chipman, 1996). In essence, our results appear unaffected by different elicitation of priors on the model size. Therefore, the real money supply and the real productivity remain the robust macro determinants of the real exchange rate in Mauritius.

6. Concluding Remarks

This paper examines the robust macro determinants of the real exchange rate in Mauritius under model uncertainty by utilizing the BMA approach. The paper brings some new contributions into the literature. First, it utilizes a broader range of potential macro determinants of the real exchange rate in Mauritius. Second, it tackles the issue of model uncertainty when identifying these macro determinants of the real exchange rate. The paper does this by exploring the impact of different priors on the model size, and different priors on model coefficients on the posterior estimates. When the BMA approach is utilized this way, the paper avoids unintended consequences of eliciting inappropriate priors, and dealing sufficiently with multicollinearity issues.

The paper finds the real money supply, and the real productivity to be the robust macro determinants of the real exchange rate in Mauritius. These two robust macro determinants yield coefficient signs that are theoretically consistent. The real money supply impact on the real exchange rate negatively, whereas the real productivity impact on the real exchange rate positively. On the one hand, higher real money supply stimulates increases in the domestic price level, which in turn lowers the real exchange rate in the long run. On the other, increasing real productivity enhances the earning capacity of the labour force. This is translated into higher real demand for money, which lowers domestic price level, thereby leading to higher real exchange rate.

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Technical Appendix

The MC[3] Sampler

Throughout the paper, we utilized the birth/death MC[3] sampler, except in the case of the tessellation prior[10]. This section provides a technical description of this sampler. The MC[3] sampler performs very well in the BMA setting, as has been shown in numerous studies. In essence, the MC[3] sampler is designed such that it wanders efficiently around the model space to observe models with non-negligible posterior mass (see Crespo Cuaresma *et al.*, 2014). The literature offers other MC[3] samplers such as the reversible-jump sampler, and the enumeration sampler but we preferred the birth/death sampler due to its approach to choosing covariates in the model space. The iteration is done such that one of the covariates is randomly selected at a time. Given that the covariate selected is already included in the present model, say M_i, it holds that the candidate model, say M_j will contain the same set of covariates as M_i except that the selected covariate will be discarded. Given that the covariate selected is not in M_i, then the candidate model will contain all the covariates from M_i in addition to the selected covariate (see Feldkircher and Zeugner, 2015). The sampled candidate model can be compared to the current model by calculating the posterior odds ratio, which gives rise to the acceptance probability as

$$\hat{p}_{ij} = min \left[1, \frac{p(M_i)p(Y|M_i)}{p(M_j)p(Y|M_j)} \right]$$

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[10] See George (2010) for a technical description of the tessellation MC[3] sampler.

Data Appendix

| Variable	Full Name	Source
RER	Real effective exchange rate	Word Development Indicators
GCR	The ratio of government consumption to GDP	Word Development Indicators
OPEN	Trade openness	Word Development Indicators
TOT	Terms of trade	Word Development Indicators
NFAR	Net foreign assets to GDP	Word Development Indicators
WGDPG	The world economic growth	Word Development Indicators
RCPI	Real commodity price index	Global Economic Monitor
RMS	Real Money Supply	Word Development Indicators
URIR	Real interest rate (%)	Word Development Indicators
RDP	Real FDI	Word Development Indicators
RGDP	GDP (constant 2005 US$)	Word Development Indicators
GFCF	Gross fixed capital formation (constant 2005 US$)	Word Development Indicators
INF	Inflation, consumer prices (annual %)	Word Development Indicators
AVI	Real Average Maturity	Word Development Indicators
RAM	Average interest on new external debt commitments, official (%)	Word Development Indicators
RDS	Real Debt Service	Word Development Indicators
IMP	Imports of goods and services (constant 2005 US$)	Word Development Indicators
EXP	Exports of goods and services (constant 2005 US$)	Word Development Indicators
IVA	Industry, value added (constant 2005 US$)	Word Development Indicators
RIP	Real Interest Payments	Word Development Indicators
MVA	Manufacturing, value added (constant 2005 US$)	Word Development Indicators
RODA	Real Net official development assistance and official aid received	Word Development Indicators

Table 1: The definition and source of each of the variables we used in this paper. They are of two categories. The first category includes variables that are frequently identified as the determinants of the real exchange rate. The second includes variables that may also influence the real exchange rate.

	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
LNRMS	0.9975	-0.4772	0.0898	0.9972	-0.4768	0.0906	0.9971	-0.4771	0.0903	0.9969	-0.4805	0.0956
LNRGDP	0.9459	0.7484	6.1075	0.9437	0.7456	6.4620	0.9454	0.7490	6.2339	0.9305	0.7879	8.2211
NFAR	0.2323	-0.0002	0.0005	0.2333	-0.0002	0.0005	0.2315	-0.0002	0.0005	0.2810	-0.0003	0.0005
URIR	0.1933	-0.0008	0.0019	0.1940	-0.0008	0.0019	0.1915	-0.0007	0.0019	0.2397	-0.0010	0.0021
LNMVA	0.1180	-0.0522	0.2484	0.1205	-0.0541	0.2529	0.1166	0.0762	0.3481	0.1492	-0.0695	0.2855
LNIVA	0.1171	0.0760	0.3480	0.1198	0.0784	0.3530	0.1166	-0.0524	0.2489	0.1470	0.0984	0.3941
LNRIP	0.1080	0.0030	0.0130	0.1073	0.0030	0.0129	0.1057	0.0030	0.0129	0.1378	0.0041	0.0149
LNRDS	0.0952	-0.0024	0.0116	0.0953	-0.0024	0.0117	0.0947	-0.0024	0.0117	0.1208	-0.0033	0.0136
LNRODA	0.0932	-0.0011	0.0055	0.0947	-0.0011	0.0055	0.0933	-0.0011	0.0055	0.1131	-0.0013	0.0061
LNOPEN	0.0833	0.0437	6.1028	0.0850	0.0422	6.4571	0.0824	0.0446	6.2291	0.1067	0.0816	8.2157
LNRDP	0.0817	-0.0005	0.0033	0.0819	-0.0039	1.3867	0.0809	-0.0018	0.7877	0.1031	-0.0047	1.0380
LNTOT	0.0799	-0.0015	0.7703	0.0817	-0.0005	0.0033	0.0788	-0.0005	0.0033	0.1003	-0.0109	1.7609
LNEXP	0.0776	-0.0048	1.3128	0.0816	-0.0012	0.8158	0.0777	-0.0045	1.3367	0.0992	-0.0005	0.0037
LNRCPI	0.0766	-0.0032	0.0246	0.0768	-0.0032	0.0247	0.0757	-0.0031	0.0245	0.0948	-0.0038	0.0278
LNGFCF	0.0741	-0.0034	0.0378	0.0751	-0.0034	0.0383	0.0727	-0.0034	0.0374	0.0937	-0.0042	0.0436
LNINF	0.0724	-0.0006	0.0038	0.0744	-0.0380	5.0879	0.0715	-0.0400	4.9095	0.0917	-0.0700	6.4748
LNIMP	0.0721	-0.0387	4.8068	0.0709	-0.0006	0.0038	0.0711	-0.0006	0.0038	0.0913	-0.0007	0.0044
LNRAM	0.0694	-0.0014	0.0155	0.0689	-0.0014	0.0155	0.0693	-0.0014	0.0155	0.0882	-0.0019	0.0180
LNGCR	0.0622	0.0100	0.1633	0.0629	0.0000	0.0007	0.0621	0.0101	0.1636	0.0789	0.0132	0.1896
AVI	0.0619	0.0000	0.0007	0.0628	0.0099	0.1648	0.0615	0.0000	0.0007	0.0788	0.0000	0.0008
WGDPG	0.0607	0.0000	0.0006	0.0606	0.0000	0.0006	0.0595	0.0000	0.0006	0.0776	0.0000	0.0007

Table 2: Each column shows the PIPs, PMs, and PSDs based on four different flexible Zellner's g prior structures. These are the uniform information prior, the risk information criterion, the benchmark prior suggested by Fernández et al. (2001), and the local empirical Bayes prior. All computations are based on and 6,000,000 posterior draws and 3,000,000 burn-ins.

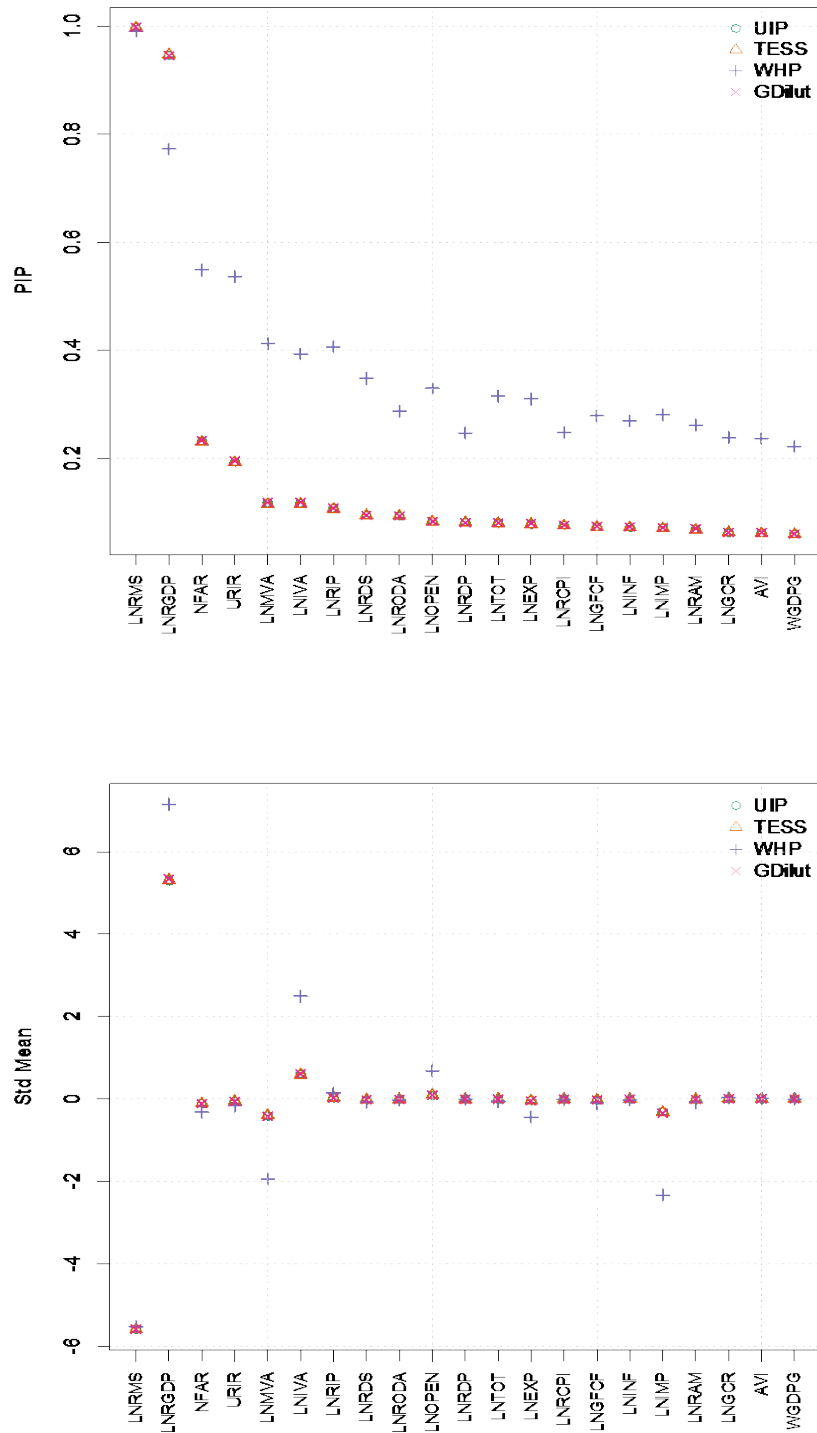|	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD	PIP	PM	PSD
LNRMS	0.9975	-0.4772	0.0898	0.9973	-0.4771	0.0901	0.9905	-0.4712	0.1326	0.9973	-0.4771	0.0903
LNRGDP	0.9459	0.7484	6.1075	0.9474	0.7511	6.2198	0.7728	1.0110	14.9982	0.9452	0.7553	6.4707
NFAR	0.2323	-0.0002	0.0005	0.2306	-0.0002	0.0005	0.5486	-0.0006	0.0008	0.2331	-0.0002	0.0005
URIR	0.1933	-0.0008	0.0019	0.1927	-0.0008	0.0019	0.5367	-0.0023	0.0030	0.1956	-0.0008	0.0019
LNMVA	0.1180	-0.0522	0.2484	0.1162	0.0735	0.3411	0.4126	-0.2443	0.4974	0.1192	0.0767	0.3490
LNIVA	0.1171	0.0760	0.3480	0.1150	-0.0504	0.2444	0.4069	0.0140	0.0252	0.1187	-0.0529	0.2492
LNRIP	0.1080	0.0030	0.0130	0.1064	0.0030	0.0129	0.3931	0.3114	0.6566	0.1087	0.0031	0.0130
LNRDS	0.0952	-0.0024	0.0116	0.0944	-0.0024	0.0116	0.3479	-0.0112	0.0246	0.0943	-0.0024	0.0117
LNRODA	0.0932	-0.0011	0.0055	0.0937	-0.0011	0.0055	0.3297	0.3547	14.9916	0.0935	-0.0011	0.0055
LNOPEN	0.0833	0.0437	6.1028	0.0830	0.0460	6.2151	0.3152	-0.0205	1.8878	0.0834	0.0508	6.4659
LNRDP	0.0817	-0.0005	0.0033	0.0813	-0.0005	0.0033	0.3100	-0.0522	3.2494	0.0813	-0.0005	0.0033
LNTOT	0.0799	-0.0015	0.7703	0.0800	-0.0019	0.7850	0.2872	-0.0027	0.0100	0.0812	-0.0025	0.8166
LNEXP	0.0776	-0.0048	1.3128	0.0783	-0.0050	1.3357	0.2808	-0.2931	11.7923	0.0795	-0.0059	1.3891
LNRCPI	0.0766	-0.0032	0.0246	0.0753	-0.0031	0.0244	0.2788	-0.0116	0.0831	0.0770	-0.0032	0.0247
LNGFCF	0.0741	-0.0034	0.0378	0.0730	-0.0032	0.0373	0.2695	-0.0024	0.0080	0.0743	-0.0033	0.0378
LNINF	0.0724	-0.0006	0.0038	0.0722	-0.0006	0.0038	0.2617	-0.0070	0.0328	0.0733	-0.0006	0.0038
LNIMP	0.0721	-0.0387	4.8068	0.0707	-0.0408	4.8964	0.2481	-0.0080	0.0470	0.0726	-0.0447	5.0941
LNRAM	0.0694	-0.0014	0.0155	0.0677	-0.0013	0.0152	0.2471	-0.0004	0.0057	0.0701	-0.0014	0.0157
LNGCR	0.0622	0.0100	0.1633	0.0630	0.0102	0.1644	0.2387	0.0445	0.3621	0.0628	0.0101	0.1653
AVI	0.0619	0.0000	0.0007	0.0613	0.0000	0.0007	0.2368	0.0002	0.0014	0.0627	0.0000	0.0007
WGDPG	0.0607	0.0000	0.0006	0.0600	0.0000	0.0006	0.2225	-0.0001	0.0012	0.0601	0.0000	0.0006

Table 3: Each column shows the PIPs, PMs, and PSDs based on four different model prior structures. These are the uniform information prior, the tessellation prior, the weak heredity prior, and the general dilution prior. All computations are based on and 6,000,000 posterior draws and 3,000,000 burn-ins.
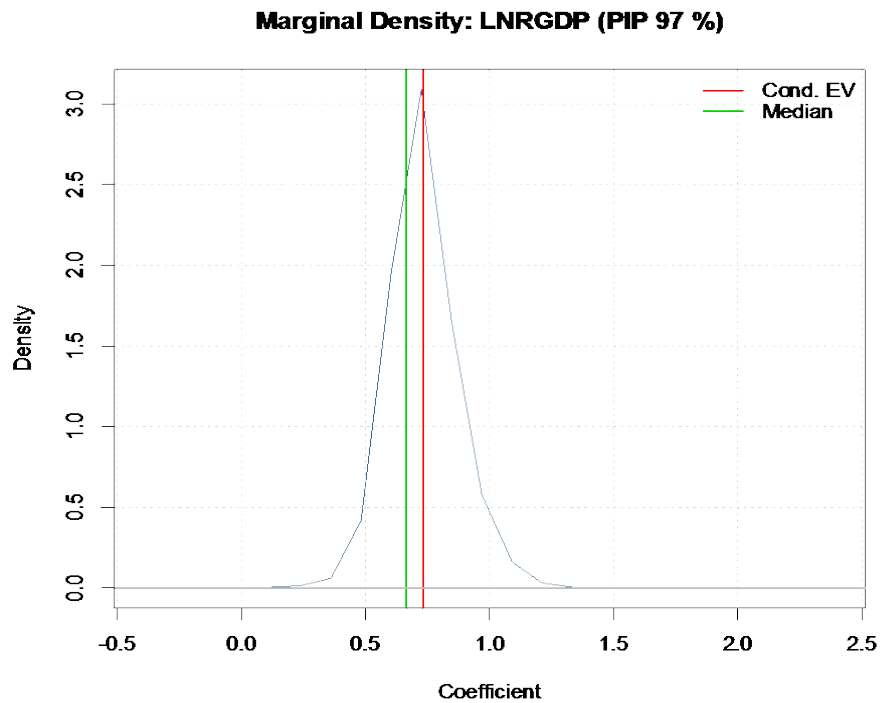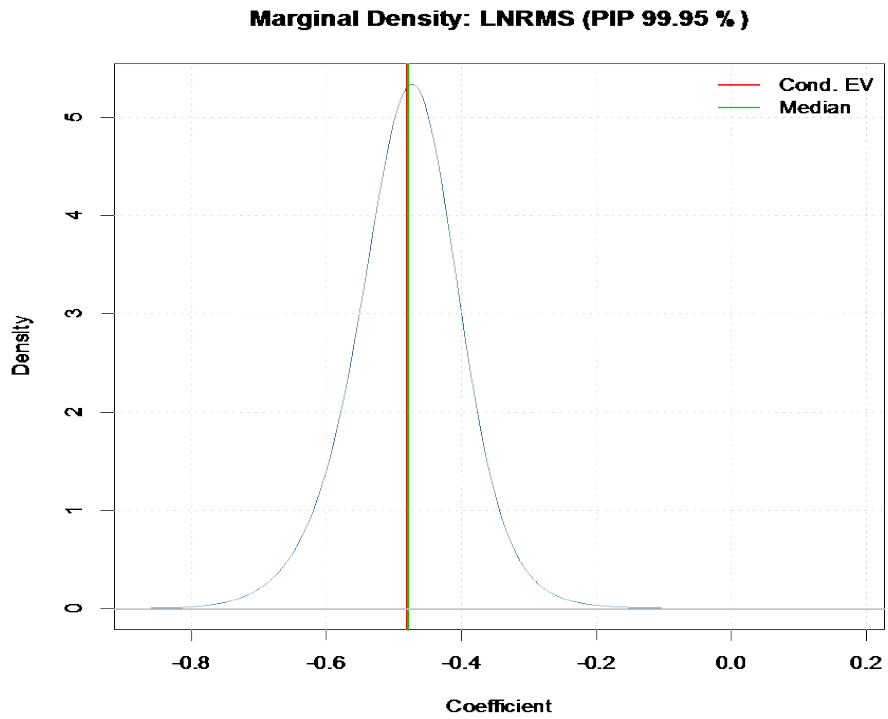
Figure 1: Unconditional posterior distribution of 5000 best models based on the Binomial-Beta distribution and flexible Zellner's g=UIP. The upper panel shows the posterior distribution of the real money supply (LNRMS). The lower panel shows the posterior distribution of the real productivity (LNRGDP).

Figure 2: Posterior inclusion probabilities and standardized coefficients based on four different flexible Zellner's g prior structures. UIP=uniform information prior, RIC=risk information criterion, BRIC=the benchmark prior suggested by Fernández *et al.* (2001), and EBL=local empirical Bayes prior.

Figure 3: Posterior inclusion probabilities and standardized coefficients based on four different model prior structures. UIP=uniform information prior, TESS=tessellation prior, WHP=weak heredity prior, and GDilut=general dilution prior.

Posterior Density of the Shrinkage Factor

Model Inclusion Based on Best 5000 Models
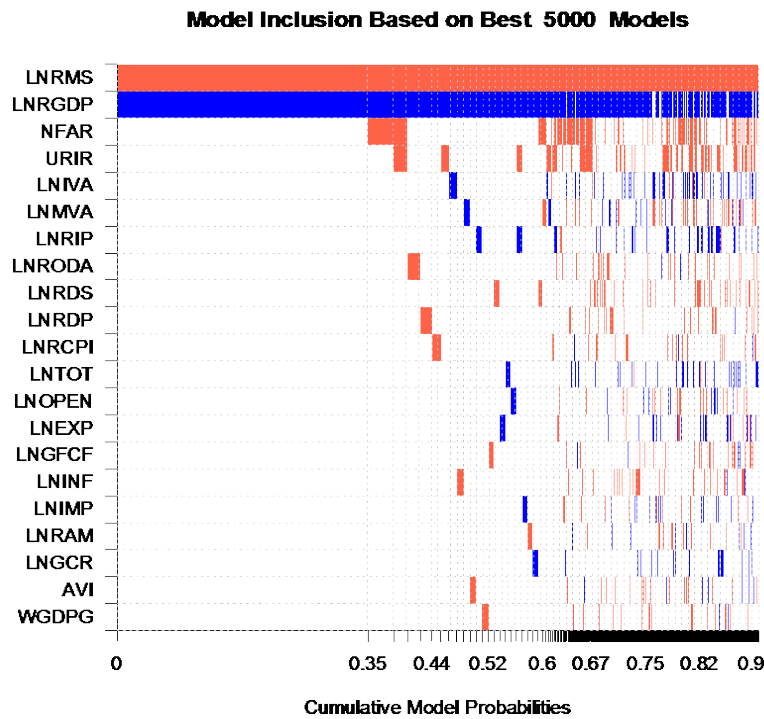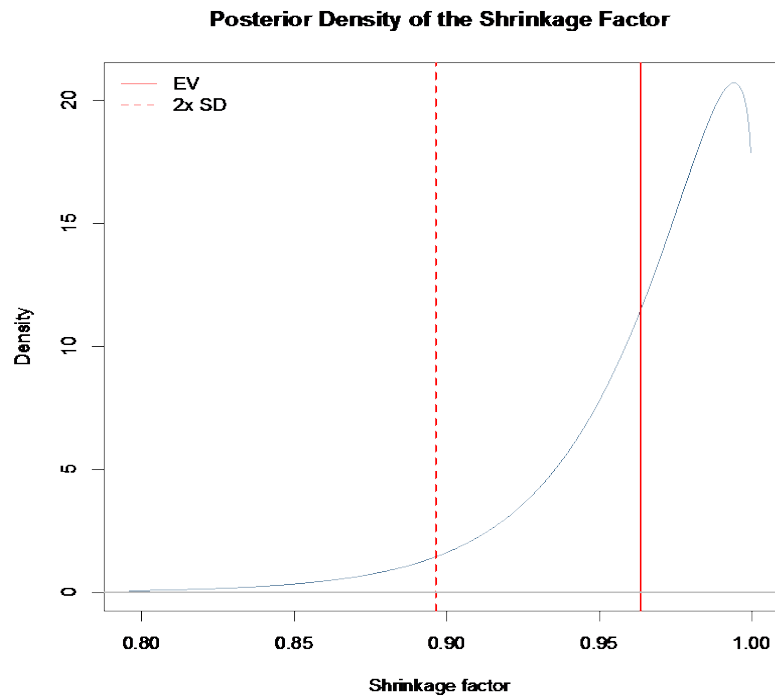
Figure 4: The upper panel shows the posterior density of the shrinkage factor. The solid line corresponds to the expected value, the dashed line correspond to a ±2 standard deviation interval. The lower panel shows the image plot of posterior coefficient signs. The blue color corresponds to a positive coefficient, red to a negative coefficient.