Finite mixture of regression modeling for exchange market pressures during the financial crisis: A robust Bayesian approach to variable selection

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Abstract

We propose a Bayesian variable selection approach in a finite mixture regression model with t-errors, which can simultaneously accommodate model uncertainty, population heterogeneity, and outliers. In particular, we adopt a spike and slab prior to deal with highly correlated covariates that are pervasive in large datasets. A Monte Carlo simulation study is conducted to examine the ability of the proposed method to correctly identify the important variables under a number of scenarios for collinear covariates. For the empirical application of exchange market pressures, we identify two clusters of countries that do not match with any country-specific dummies. We find that a number of early warning indicators are robust to heavy-tailed distributions and exert differential impacts on external market pressures across the two groups of countries. In contrast to the earlier 2008-crisis literature, we present optimistic view with regard to the feasibility of an early warning system to predict the likelihood of crises. We also identify outlying countries—most notably Seychelles—in explaining exchange market pressures in a cross-section of countries.

`Keywords`: Financial crisis, Robust Variable Selection, Heteroscedasticity, Outliers, Finite Mixture Models.

`JEL classification`: C11, C21, C52, F31, O50.

1 Introduction

The percussion of the global crisis in 2008 has rekindled academic interest in early warning models (see, e.g., Frankel and Saravelos, 2012; Rose and Spiegel, 2010, 2011, 2012, among others). Researchers have sought to identify risk factors that can indeed predict crisis occurrences. On the other hand, economic theory offers little guidance about the appropriate set of variables included in the underlying true model. Thus, a challenging question is to determine, out of an often large set of candidate variables with a limited number of observations, the variables relevant for crisis events. In contrast to the classical inference, the Bayesian approach provides a natural and general probabilistic framework that simultaneously treats both model and parameter uncertainty (Clyde and George, 2004). To address this uncertainty in the context of financial crisis early contributions have applied Bayesian model averaging (BMA) (e.g., Cuaresma and Slacik, 2009; Dwyer and Tan, 2014; Feldkircher et al., 2014; Ho, 2014).

All the mentioned contributions are, however, plagued by a number of sensitivity issues that determine the relationship between the crisis intensity and the covariates for all considered countries or regions. In particular, the usually considered data sets that comprise very heterogeneous countries or regions make the assumption of a common marginal impact of external shocks, even when controlling for a variety of risk factors, at least worth investigating (Doppelhofer and Weeks, 2011; Ho, 2014; Temple, 2000). Despite the wide applicability of the linear regression model powered by the modern variable selection tools, a single regression model can be inadequate if the data come from a heterogenous population that consists of a number of different sub-populations with different characteristics. In this situation, it is possible that a separate linear regression model is needed for each sub-population, moreover, the regression models in different sub-populations may use different subsets of covariates to explain the response variable. If the memberships of the observations are unobserved, then we naturally have a finite mixture model of linear regressions, where each mixture component is a linear regression model with its own subset of covariates. This gives rise to a variable selection problem that is more complex than that of a single linear regression model.

In this paper, we propose a flexible Bayesian modeling with a finite mixture regression (FMR) model to investigate the robustness of the determinants of the crisis intensity, particularly exchange market pressures during the recent global financial crisis. In FMR models, the characteristics corresponds to the effects of covariates which vary with subpopulations. It implies that the changes of response may be affected by different sets of covariates in the FMR models. Our Bayesian approach is flexible to account for model uncertainty and allow for various forms of heterogeneity. In the Bayesian framework, a popular choice of prior has been Zellner's (1986) g-prior for the regression coefficients which is based on the inverse of empirical covariance matrix of the covariates. However, the difficulties can arise in variable selection when covariates are highly correlated (Clyde and George, 2004; Liang et al., 2008). Instead of g-prior, a spike and slab prior (George and McCulloch, 1993) is considered here to perform variable selection in the presence of correlated covariates.[1] In particular, it is straightforward to explicitly incorporate prior information for the relative importance of covariates with a spike and slab prior. Furthermore, to prevent the statistical inferences from being distorted by the presence of outliers, a FMR model with t errors is proposed.

Our results from the proposed variable selection show that two distinct groups of countries differ in the effects of leading indicators on external market pressures, rendering constant parameter regressions invalid when analyzing the cross-country incidence and severity of global crisis. We also identify a number of important pre-crisis indicators different from the previous studies in rankings and signs. First, for the top ranked variable, our result

[1]See also Korobilis (2013) in forecasting output and inflation series.

emphasizes the essential role of growth rate prior to the crisis played in explaining exchange market pressures. Overheated economy could have elevated the country vulnerability to external shocks. Second, we find the degrees of globalization affect exchange market pressures across two clusters of countries, and the effect is particularly evident for the second cluster of countries. Third, we do not find supportive evidence for grouping dummies of country-specific characteristics, implying the FMR model with two clusters is sufficient in uncovering the patterns of exchange market pressures. Finally, a number of countries, including China, Mauritania, Seychelles, Venezuela, and the U.S., are considered as potential outliers. A series of robustness checks suggests that our results are not qualitatively changed by taking into account the effects of outliers and collinearity.

This paper is organized as follows. We briefly review the empirical literature in the early warning models, with a focus of the Bayesian approaches for model uncertainty in Section 2. We introduce the FMR models in Section 3. The prior distributions and a fully Bayesian approach employed to the problem of variable selection are also discussed. We assess the performance of our proposed variable selection method in the presence of collinear covariates in Section 4. We then present the empirical results from applying our proposed method to the data on exchange market pressures in Section 5. We conclude this study in Section 6. Details of the full conditional distributions and the required MCMC algorithms are given in Appendix A.

2 Model Uncertainty in Cross-Country Crisis Intensity

A growing body of literature has investigated whether pre-crisis conditions and global factors can explain the different impact of the 2008 financial crisis in various countries. Obstfeld et al. (2009, 2010) pioneer the study on the global financial crisis in 2008 and suggest that the excessive reserves plays a major role in currency depreciation over 2008. Although the factor is established on a solid theoretical model, its empirical support is weakened by the small sample of countries. In a series of papers, Rose and Spiegel (2010, 2011, 2012) consider a large number of potential explanatory variables for the crisis that have been discussed in the literature, covering such "fundamentals" as: financial system policies and conditions, asset price appreciation in real estate and equity markets, international imbalances and foreign reserve adequacy, macroeconomic policies, and institutional and geographic features. Surprisingly, they find that pre-crisis macroeconomic and financial conditions generally fail to explain the economic performance of countries during the crisis period. There are a few exceptions, however, including run-ups in asset prices and current account deficits prior to the crisis, which were both significantly correlated with the crisis severity. Their general finding of inconclusive relationships presents a pessimistic view with regard to the feasibility of an early warning system to predict the timing of such crises. In contrast, in an extensive review of the early warning indicators literature, Frankel and Saravelos (2012) find that the pre-crisis level of reserves and preceding real exchange rate appreciation are consistently useful in predicting exchange market pressures, in particular, Frankel and Saravelos (2012) emphasize a more positive role for reserves than other recent studies in reducing vulnerability of developing countries.

Recently, Aizenman et al. (2012) investigate the determinants of EMP by focusing on emerging markets (EMs) during the 2008–09 crisis.[2] The authors find that per capita income prior to the financial crisis (as of 2007), inflation and the trade balance appear as useful leading indicators that can explain cross-country difference in EMP.

[2] Aizenman et al. (2012, p. 600) note that "EMP was a major component of the financial stress in EMs during the 2008–9 crisis, while it played virtually no role in the preceding episodes."

The past studies on the early warning indicators produce mixed evidence about EMP determinants, which may be partly due to the methodological flaws in neglecting model uncertainty and the attendant omitted variable bias. It is common practice for empirical studies to conduct a horse race of linear regressions from some class of early warning models *a priori* and then make inferences as if the selected were the 'true' model. As Raftery (1995, p. 113) notes "In this situation, the standard approach of selecting a single model and basing inference on it underestimates uncertainty about quantities of interest because it ignores uncertainty about model form." The early warning models have received much discussion in the literature, the role of model uncertainty, while essential, is only rarely addressed. There are, however, several notable exceptions in which BMA techniques are used to account for model uncertainty in early warning regressions (Babecky et al., 2013; Cuaresma and Slacik, 2009; Feldkircher et al., 2014).[3] Feldkircher et al. (2014) consider an extensive set of pre-crisis leading indicators and explicitly account for the issue of model uncertainty in EMP. Surprisingly, only two leading indicators—inflation and the joint record of domestic savings—stand out as robust determinants of exchange rate pressures. With the updated dataset of Frankel and Saravelos (2012), the BMA evidence of Christofides et al. (2013) supports a number of early warning signals that are significantly correlated with exchange rate pressure, including real effective exchange rate, remittances, trade deficits, bank liquidity-to-asset ratios and levels of domestic credit.

Nevertheless, all of the studies reviewed above assume constant parameters in their linear regressions, even though the country heterogeneity in the responses to external shocks were well noted by the authors (e.g., Aizenman et al., 2012; Feldkircher et al., 2014). In particular, Temple (2000) forcefully argues that, other than model uncertainty, parameter

[3] A general overview of BMA refers to Doppelhofer (2008); Hoeting et al. (1999); Raftery et al. (1997). For special emphasis on the applications of BMA to economics refers to Moral-Benito (2013).

heterogeneity and outliers have not received adequate attention in the empirical literature. It is of paramount importance to control cross-country heterogeneity in the current empirical literature. Durlauf (2000) points out two major drawbacks without proper treatment of heterogeneity. First, *ad hoc* country groupings may be inconsistent with the true underlying grouping. Second, while fixed effects estimation allows for heterogeneity through the intercept, most studies do not allow for heterogeneity in the slope parameters. In the context of growth models, the effects of covariates such as inflation and investment are assumed to be homogeneous across (groups of) countries. Although the homogeneity simplifies the estimation greatly, it often becomes quite restrictive in an increasingly diverse world economy. Heterogeneity, on the other hand, could be generated by outliers, which is likely to encounter in a large-scale cross-country dataset. Outliers can be seen as the deviations from the typical empirical relationship implied by the regression of dependent variables to independent variables, and they can be caused by fat-tailed or asymmetric error distributions, measurement errors, or model mis-specifications (Sturm and de Haan, 2005). As a result, the presence of outliers can adversely affect the statistical inference or even obscure the true relationship. Several recent works have adopted the robust Bayesian estimation to account for potential outliers. To name a few, Doppelhofer and Weeks (2011) consider the case of the cross-country economic growth, and Ho (2014) investigates the cross-country causes of the 2008-09 crisis. They both highlight the impact of potential outliers on BMA, and to the extent that the major findings can be significantly altered by the robust estimation. To address these issues, we propose a flexible Bayesian modelling to simultaneously account for model uncertainty, population heterogeneity and outliers, while systematically choosing the subset of early warning indicators that are significantly correlated with external market pressures.

3 Finite Mixture Model

FMR models have recently become a popular statistical method for modeling unobserved population heterogeneity, see, e.g., Frühwirth-Schnatter (2006); McLachlan and Peel (2000), due to the fact that they offer more natural modeling for the population consisting of different subpopulations. These subpopulations may require different parameters to adequately capture their distinct characteristics. In FMR models, the characteristics corresponds to the effects of covariates which vary with subpopulations. It implies that the changes of response may be affected by different sets of covariates in the FMR models. By and large, it becomes a variable selection problem within each subpopulation.

More recently, Bayesian variable selection approach has been extensively developed to identify the important variables, particularly in the regression analysis when the number of available covariates is moderately large, but only a subset of variables are relevant to explain variation in the data, see, e.g., Khalili (2011) for review. We apply a Bayesian variable selection to FMR models, where variable selection procedure is implemented to select the important covariates in each subpopulation. In FRM, the regression coefficients may change across subpopulations. Whenever the information is available about the nature of heterogeneity for the problem at hand, it can be incorporated by choosing a specific probabilistic specification for β, which is pre-specified in terms of the density of $\pi(\beta)$ as a prior distribution, imposing some model structure on the individual regression coefficients that may be dominated by the information in the data. Different prior distributions defining different model structures may be compared in a systematic way by Bayesian model comparisons.

To fix notation, let (y_i, x_i), $i = 1, \ldots, n$, be a data set of n observations that come from a heterogeneous population, where y_i is the response variable of the i-th observation, and $x_i = (x_{i1}, x_{i2}, \ldots, x_{ip})'$ collects the p covariates of the i-th observation. We assume that the heterogeneous population consists of M sub-populations or mixture clusters, and within each sub-population, (y_i, x_i) is fitted by a separate linear regression model. Specifically,

$$y_i|\beta_m, \sigma_m^2, \rho_m, \omega_i \sim \sum_{m=1}^{M} \rho_m \cdot N\left(x_i'\beta_m, \omega_i\sigma_m^2\right). \tag{1}$$

Here $\rho_m = (\rho_1, \ldots, \rho_M)$ describes the proportions of the population distributed among M clusters, or the the mixing proportions, and $\rho_m \geq 0$ and $\sum_{m=1}^{M} \rho_m = 1$, and let $\beta_m = (\beta_{m1}, \ldots, \beta_{mp})'$ be the coefficient vector for the mth cluster. We assume that the cluster is normally distributed with a mean $x_i'\beta_m$ and a variance $\omega_i\sigma_m^2$, where ω_i is the variance-inflation factor corresponding to the ith observation and therefore the error variances vary across countries. The model is also flexible enough to place a specific prior on ω_i to accommodate outliers and select relevant covariates simultaneously (Geweke, 1993). The main interest is to identify the covariates x_{mp}'s that one believes to have an influence on the response variables y_i in cluster m. To solve this problem within the Bayesian framework, we introduce two set of latent variables. For the first set of latent variables, each observation is associated with an indicator, determining which sub-population or mixture cluster this observation comes from. For the second set of latent variables, within each mixture cluster, each covariate is associated with an indicator, determining whether this variable is included in the regression model of the mixture cluster.

The first latent variable z_i is defined as follows

$$z_i = m, \text{if } y_i \sim N\left(x_i'\beta_m, \omega_i\sigma_m^2\right), m = 1, \ldots, M,$$

with $P(z_i = m) = \rho_m$ for $i = 1, \dots, n$. That is,

$$z_i \sim \text{Multinomial}(\rho_1, \dots, \rho_M).$$

Given $z = (z_1, \dots, z_n)$, the joint density of (y, z) can be written as follows

$$f(y, z|\theta) = \prod_{i=1}^{n} \rho_{z_i} N\left(x_i' \beta_m, \omega_i \sigma_m^2\right),$$

where $\theta = \{\beta_1, \dots, \beta_M, \sigma_1^2, \dots, \sigma_M^2, \rho_1, \dots, \rho_M, \omega_1, \dots, \omega_n\}$. Conditioning on the latent variable z_i, the cluster to which each observation belongs is known, and therefore, the Bayesian variable selection method is straightforward to carry out for each cluster in the FMR model.

Another latent vector r_m is used to identify active variables for each regression model in each cluster of the mixture model. It is equivalent to identify the non-zero elements in β_m for each m. In order to perform the variable selection, for the mth cluster, we define a $p \times 1$ vector $r_m = (r_{m1}, \dots, r_{mp})'$ so that for covariate x_j in cluster m, $\beta_{mj} = 0$ if $r_{mj} = 0$ and $\beta_{mj} \neq 0$ if $r_{mj} = 1$. Therefore, given r_m, let $\beta_m(r_m)$ consist of all nonzero elements of β_m and let $x(r_m)$ be the active elements of x corresponding to those elements of r_m that are equal to 1. Thus, the FMR model in equation (1) can be re-written as

$$y_i|\beta_m, \sigma_m^2, \rho_m, r_m, \omega_i \sim \sum_{m=1}^{M} \rho_m \cdot N\left(x_i(r_m)'\beta_m(r_m), \omega_i \sigma_m^2\right).$$

Based on the augmentation of these two sets of indicators, it allows one to transform the complex structure of mixture model into a set of simple structures, so that in the Bayesian analysis the Gibbs sampler can be easily implemented to draw the sample from the posterior distribution. In the following subsections, we first introduce the prior specifications, and then describe the implementation details of our proposed Bayesian approach.

3.1 Priors

We first consider the mixing proportion vector ρ. Similar to Viele and Tong (2002), we assume a conjugate Dirichlet prior distribution for ρ

$$\rho \sim \text{Dirichlet}(\alpha_1, \ldots, \alpha_M).$$

In each component of mixture regression model, the prior of the indicator variable r_{mj} is independently Bernoulli(d_{mj}) for $j = 1, \ldots, p$. As a result, the joint density of $r_m = (r_{m1}, \ldots, r_{mp})'$ is

$$\pi(r_m) = \prod_{j=1}^{p} d_{mj}^{r_{mj}} (1 - d_{mj})^{1-r_{mj}}.$$

Consider the spike and slab prior for the coefficient vector β_m. That is, given r_m, the prior of the regression coefficient vector, β_{mj} for all j and m is assumed to be

$$\beta_{mj} | r_{mj} \sim (1 - r_{mj})\delta_0 + r_{mj} N(0, \tau_{mj}^2),$$

where δ_0 is a point mass at 0.

To eliminate the selection bias on τ_{mj}, we further assume τ_{mj}^2 independently distributed $IG\left(\frac{a_{\tau_{mj0}}}{2}, \frac{b_{\tau_{mj0}}}{2}\right)$. To address the effect of outliers on the estimation and statistical inference, we place a specific prior on ω_i which follows a inverse Gamma distribution, $IG(v/2, v/2)$. Under this setting, the linear model is equivalent to a model whose errors have independent and identical Student-t distributions with the degree of freedom equal to v, as in Geweke (1993). Note that lower values of v correspond to heavy-tailed distributions and hence more

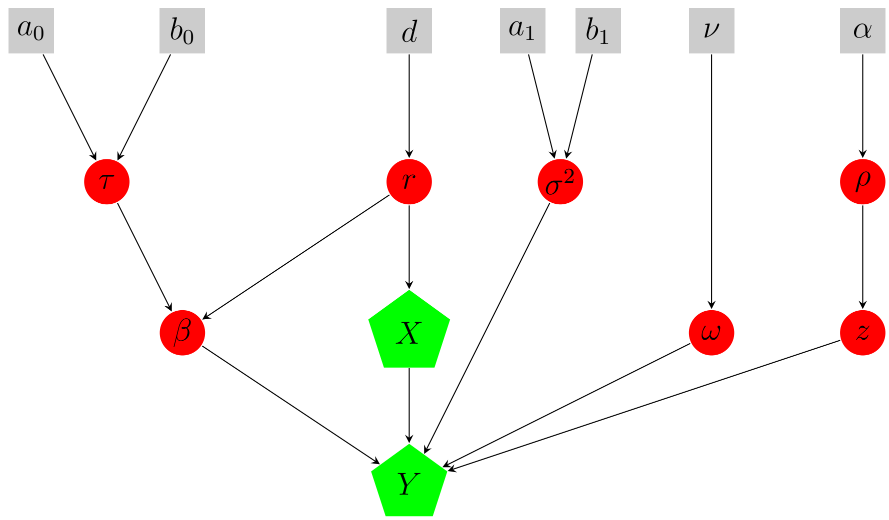

Figure 1: The figure illustrates the hierarchical structure of the priors on the parameter of the proposed model. A green pentagon indicates the observed data, a red circle indicates the latent variables or parameters to be estimated, and a gray square indicates a hyper-parameter, which is considered to be a constant for the corresponding prior distribution. The arrows indicate the conditional dependence structure of the model.

accommodating of outliers, and also imply relatively larger variances in the inverse Gamma distribution.

As usual, an independent inverse Gamma distribution, $IG\left(\frac{a_{m_0}}{2}, \frac{b_{m_0}}{2}\right)$, is placed on σ_m^2, that is,

$$p(\sigma_m^2|a_{m_0}, b_{m_0}) \propto (\sigma_m^2)^{-\frac{a_{m_0}}{2}-1} \exp\left\{-\frac{b_{m_0}}{2\sigma_m^2}\right\}.$$

We assume $r, \sigma, \rho, \tau, \omega$ are *a priori* independent, β conditionally independent. A hierarchical representation of our Bayesian model is shown in Figure 1.

3.2 Posterior estimation

Under the model and prior specifications laid out in the above section, the joint posterior distribution can be derived. The posterior distribution is not available in explicit form so we use the MCMC method, specifically Gibbs sampling (Brooks et al., 2011) to simulate the parameters from the posterior distribution. To implement the Gibbs sampler, the full conditionals of all parameters must be determined. A derivation of the full conditional distributions is provided in Appendix A. With the conditional probability of each parameter, the parameters in each cluster are then updated individually using a Gibbs sampler (where available), or a Metropolis-Hastings sampling algorithm.

Under mild regularity conditions and for sufficient iterations, the sample simulated from the above Gibbs sampler can be used to approximate the joint posterior distribution. We collect a sequence of MCMC samples and then approximate the posterior probability of covariate x_j within subpopulation (cluster) m by

$$\hat{p}(r_{mj} = 1|y) \approx \frac{1}{K_j} \sum_{k=1}^{K} I\{r_{mj}^{(k)} = 1\}. \tag{2}$$

This gives an estimate of the posterior inclusion probability (PIP) as a measure of the relative importance of the jth covariate within cluster m. Higher posterior inclusion probabilities indicate the covariate is important in explaining the response variable for the mth cluster.

A researcher may also be interested in drawing inference about the economic importance of a variable in terms of posterior estimates. Both can be approximated in a straightforward manner from the corresponding PIP. The posterior mean for the regression coefficient β_j

associated with covariate x_j, for cluster $m = 1, \ldots, M$.

$$\mathrm{E}(\beta_{mj}|\boldsymbol{y}) = \sum_{r_{mj}} \mathrm{E}\left[\beta_{mj}|r_{mj}, \boldsymbol{y}\right] p\left(r_{mj}|\boldsymbol{y}\right) \approx \frac{1}{K_j} \sum_{k=1}^{K} \beta_{mj}^{[k]},$$

where K is the number of samples generated from the posterior distribution using the MCMC procedure. Moreover, $r_{mj}^{[k]}$ and $\beta_{mj}^{[k]}$ is the MCMC sample in the kth iteration, and $K_j = \sum_{k=1}^{K} r_{mj}^{[k]}$.

4 Simulation study

In this section, we conduct several simulation experiments to validate our proposed model and the estimation procedure described above. This is done to examine the degree of accuracy on selecting the important variables. In particular, we investigate the potential impacts of severe and complicated collinearity in the design matrix.

4.1 Simulation Settings

We consider a simple situation to illustrate the important properties of the model and the crucial aspects of the simulation procedure. For this simulation, we assume there are two clusters and the 150×20 design matrix $\boldsymbol{X}$ follows a multivariate normal distribution with a mean of 0. We consider four pair correlation structures with $\mathrm{corr}(x_i, x_j) = 0, 0.5, 0.75, 0.95$ for covariates i and j, $i \neq j$. The parameters of the model are randomly generated from the following distributions:

$$\begin{aligned}
\rho &\sim \text{Dirchlet}(3,3) \\
r_{mj} &\overset{iid}{\sim} \text{Bernoulli}(0.5) \\
\tau_{mj}^2 &\overset{iid}{\sim} IG(2,2) \\
\beta_{mj}|r_{mj},\tau_{mj} &\overset{iid}{\sim} (1-r_{mj})\delta_0 + r_{mj}N(0,\tau_{mj}^2) \\
\sigma_m^2 &\overset{iid}{\sim} IG(2,2) \\
\omega_i &\overset{iid}{\sim} IG(2,2).
\end{aligned}$$

The main point we want to address is the accuracy of our proposed model in this simulation. In addition, we would expect the proposed method to provide a sufficiently parsimonious model that contains as many active variables and as fewer noise variables as possible. In this simulation study, the median probability criterion (Barbieri and Berger, 2004) is used. That is, we estimate the posterior inclusion probability $P(r_{mj} = 1|y)$ for each covariate j within cluster m from the Monte Carlo sample shown in equation (2). We claim covariate j should be included into the model for cluster m once the posterior probability $P(r_{mj} = 1|y)$ is greater than or equal to 0.5.

To evaluate the performance of our proposed method, we consider the following measures: the accurate rate of grouping observations (ARG), the accuracy of classification of variables (ACC), the true positive rate (TPR), and the false positive rate (FPR). ARG is the rate of grouping the observations in the correct subpopulation. ACC is the ratio of variable truly classified to the number of variables. TPR is defined as the ratio of the number of true variables identified to the true number of active variables, and FPR the number of inactive variables to the number of inactive variables. These measures provide the statistical

Table 1: Simulation Study

$\text{corr}(x_i, x_j)$	0		0.5		0.75		0.95	
	t-Error	Normal	t-Error	Normal	t-Error	Normal	t-Error	Normal
ARG	0.95	0.93	0.93	0.90	0.88	0.83	0.80	0.75
ACC	0.99	0.96	0.99	0.94	0.97	0.93	0.88	0.80
TPR	1.00	0.98	0.98	0.93	0.95	0.92	0.90	0.81
FPR	0.01	0.01	0.02	0.08	0.01	0.01	0.11	0.20

The performance of our proposed variable selection approach under different cross correlations between covariates. t-Error indicates the regression errors follow a Student-t distribution with the degree of freedom of $v = 5$, whereas Normal indicates the regression errors follow a normal distribution.

assessment of the proposed approach for variable selection. Additionally, we investigate the effect of outliers on the variable selection problem. To this end, we compare all the above measures with our proposed variable selection approach while ω is assumed to be fixed and equal to 1 in equation (1).

The ARG, ACC, TPR, and FPR over 100 simulation runs for four different pair correlations between covariates are summarized in Table 1. The performance of classification by applying our proposed approach produces comparable results. Even there exists high collinearity in the design matrix, our proposed model is still able to identify important variables and well classify the observations. Additionally, when the simulated data contains observations with longer than normal tails or atypical observations, the use of mixture model with t-distribution for error terms leads to fewer misallocations.

5 Empirical Results

In order to make a comparable study, we apply our proposed Bayesian framework to the measures of exchange market pressures (EMP) analyzed in Feldkircher et al. (2014). Feldkircher et al. (2014) consider a large number of leading indicators that have been discussed in the early warning literature, covering a wide range of different factors, including data on financial conditions, foreign reserve adequacy, macroeconomic policies, institutional features, monetary policy regimes and more. The dataset is balanced and the candidate covariates are measured annually as of end-2007.[4] In total, there are 58 potential leading indicators of EMP for a broad global sample of 149 countries. We use the same variable names as in Feldkircher et al. (2014), and the full name of each variable can be found in the Appendix (Table A1).[5] The dependent variable of interest is the EMP index on a quarterly basis.[6] The EMP measure consists of the percentage change in the exchange rate (positive values denote percentage depreciation) and percentage loss of reserves.[7] Higher values of EMP indicate greater pressure of exchange market. Figure 2 presents the distribution of EMP during the recent crisis across regions of countries. It is remarkable how extreme and widespread across regions of countries were external pressures, ranging from highs experienced in Slovak Republic (101%), Venezuela (92%) and Estonia (88%) to low values for countries such as China, Bolivia and Hong Kong. This observation is consistent with Aizenman and Hutchison (2012), who find that there is considerable heterogeneity in their response. Emerging markets differ most from other country groups in the adjustment mechanism. With the "fear of reserve

[4]The data are available from `http://feldkircher.gzpace.net/pages/replication_JIMF.RData`.

[5]For details of definitions and sources for these variables, see Feldkircher et al. (2014).

[6]In this paper, we focus on two versions of EMP to capture the different aspects of external pressures facing each market during the crisis period of 2007Q3–2010Q2. The first measure is the maximum EMP during the crisis ($EMPu_{max}$), the second is the maximum EMP normalized to the average pre-crisis EMP ($EMPu_{max.0006}$). While our main discussion is based on $EMPu_{max}$, we use $EMPu_{max.0006}$ to check the consistency and robustness of our variable selection results.

[7]See, e.g., Aizenman and Hutchison (2012); Aizenman et al. (2010) for the detail on EMP.

loss", the absorption of the shock facing emerging markets was mainly through exchange rate depreciation rather than international reserves depletion.

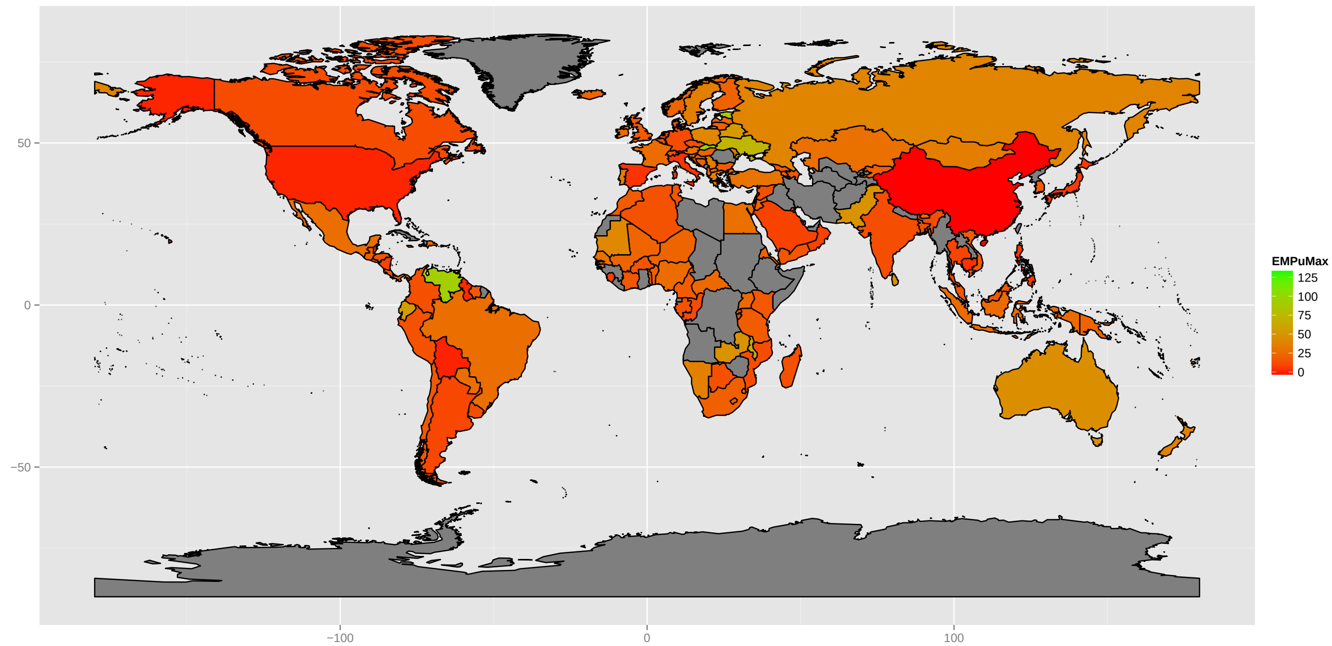

Figure 2: The distribution of EMP during the global financial crisis across regions of countries.

As the first step, we use information criteria based on the model's log likelihood to determine the number of mixture clusters m. As such, we estimate the finite mixture model for several clusters.[8] In addition to the information criteria such as the Akaike information criterion (AIC), the Bayesian information criterion (BIC) and the integrated completed likelihood information criterion (ICL; Biernacki et al. (2000)), we also consider the Corrected Akaike Information Criterion (CAIC) and the Akaike Information Criterion 3 (AIC3) for robustness as in Owen et al. (2009). The results in Table 2 show that all the information criteria are

[8]To avoid the local maximum in the EM algorithm, we try $10,000$ starting values and report the estimation results with the highest log-likelihood value. We also standardize all but dummy variables prior to analysis to facilitate convergence when the number of the considered variables is large.

consistently in favor of the model with two clusters ($m = 2$) over the linear model ($m = 1$).[9] This result suggests that the assumption of parameter homogeneity for cross-country EMP may be unrealistic. In particular, there is strong evidence against the homogeneous parameter model ($m = 1$). This result is in line with other studies on heterogeneity of exchange rate movements, such as Feldkircher et al. (2014) and Fratzscher (2009). Figure 3 show the cluster memberships for the countries included in our data set based on the posterior cluster membership probabilities. A country is assigned to a particular cluster if its estimated posterior probability of being in this cluster is greater than that of being in others.

The figure shows that the majority of countries belongs to cluster 1, while nearly 10% of countries are in another cluster.[10] It is worth noting the cluster memberships do not match with pre-defined regional segmentation or country-specific characteristics. Of those in cluster 2, many countries are severely affected by sharp drops in primary commodity exports due to falling prices and demand for their commodities (e.g., Pakistan, Venezuela, Malawi, and Belarus). The decline in export earnings along with withdrawal of short-term foreign capital are always accompanied by serious balance of payments problems. In addition, cluster 2 includes four countries adopting the euro during the crisis period (Malta, Cyprus, Estonia and Slovak Republic) which are entered as the dummy variable of **euroAdopt** in Feldkircher et al. (2014).[11]

A fixed-width approach was taken in which the MCMC scheme ran for 1 million iterations

[9] It should be noted that the models with more than two clusters fail to converge.

[10] There are 14 countries in cluster 2 spread across a number of regions, including Europe (Malta and Cyprus), Asia (Australia, Pakistan and Sri Lanka), Latin America (Ecuador and Venezuela), Africa (Malawi, Seychelles and Zambia), CIS (Belarus and Ukraine) and CEEC (Estonia and Slovak Republic).

[11] Interestingly, while this dummy is identified as a robustly important indicator with substantial posterior probability in Feldkircher et al. (2014), it only receives marginal support from our analysis. That is, the results from our proposed variable selection indicates this country-specific dummy variable does not have a significant effect on EMP. Therefore, the finite mixture model with 2 clusters can uncover the heterogeneity in EMP.

Table 2: Determination of the Number of Mixture Clusters

Number of Clusters	log-likelihood	AIC	CAIC	AIC3	BIC	ICL
1	-595.82	1311.64	1551.88	1371.64	1491.88	1491.88
2	-149.83	**541.67**	**1026.15**	**662.67**	**905.14**	**905.35**

This table present values of the information criteria for the finite mixture model with different number of clusters. The number in bold style indicates the preferred model with smallest information criteria.

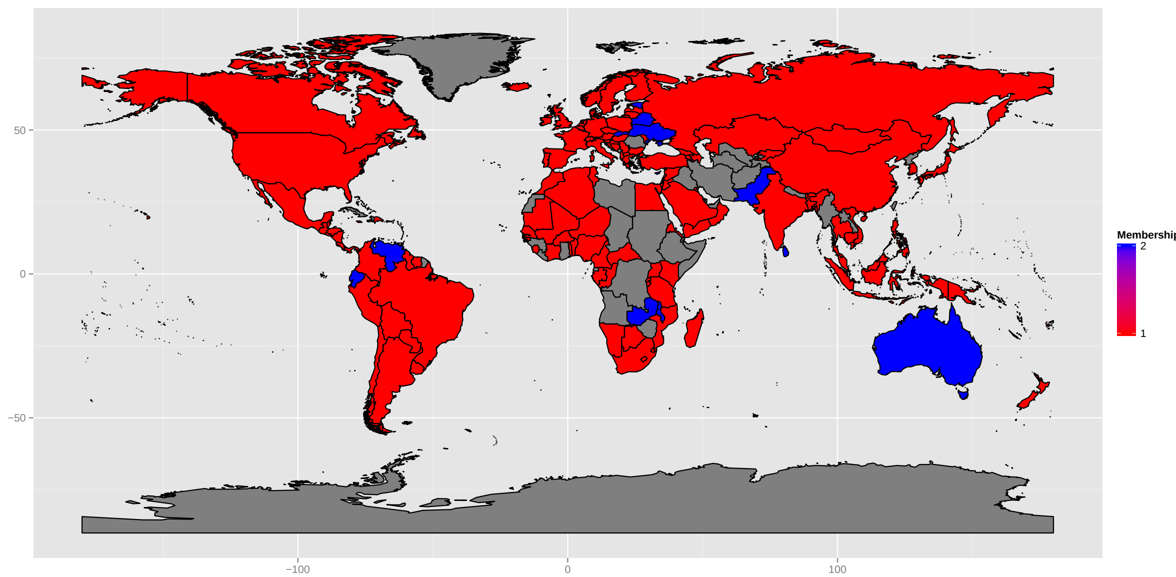

Figure 3: The posterior cluster memberships in the finite mixture model with two clusters.

to ensure MCSEs were 0.001 or smaller (Flegal et al., 2008).[12] The posterior samples are then used to estimate the posterior quantity of interest. For the sake of illustration, we only present the highest ranked leading indicators for the cross-country EMP, and the full results can be found in Appendix (Table A2).[13] For each variable we report its associated posterior inclusion

[12] In our case, the largest MCSE of the posterior probability of the indicator variable equal to 1 was less than 0.001, indicating that a sufficient number of samples were drawn.

[13] Although Feldkircher et al. (2014) consider interaction terms between the pre-crisis inflation and several variables, allowing for such interactions would lead to an impractically large model/variable space for our current application.

probability and the posterior mean of regression coefficients in Table 3. The variables are ordered based on the posterior inclusion probabilities. We consider $v = 5, 25, 100$ to see whether the results are robust to deviations from a normal distribution. If outliers are more likely to exist, a smaller value of v should be considered. While the results of variable selection are generally similar between $v = 25$ and $v = 100$, the rankings and the posterior estimates are somewhat different when $v = 5$, particularly, the sign of the regression coefficient can change with the degrees of freedom. For example, for cluster 2, **dom.credit_06** is negatively correlated with EMP for $v = 5$, whereas the opposite is produced for $v = 25$ and $v = 100$. Examples of this type include **ext.debt.exp_06**, **ext.debt.gdp_06**, **kof_cultProx_06**, **dGap_0006**, and so on. These observations suggest the outliers should be accommodated and so we restrict our main discussion to the case of $v = 5$.[14].

In Table 3, if we use the threshold value of 0.5 for posterior probability, there are 5 and 15 leading indicators across two clusters of countries, respectively, that are significantly correlated with external market pressures.[15] Although two clusters have a different set of important risk factors for the early warning models, variables shared in common include the growth rate in GDP per capita (**chg_rgdpcap0006**), the share of money supply in GDP (**money.gdp_06**), and the globalization indicators (**kof_poltGlob_06** and **kof_infFlows_06**). Of these variables, similar marginal effects are observed with different magnitudes across two groups of countries. Money supply, however, presents an opposite effect on the EMP between two clusters. The posterior estimates in Table 3 show that an increase in money supply reduces pressure on the exchange market in cluster 1 countries. By contrast, for countries in cluster 2, money supply constitutes a waste of resources for the economy, subsequently amplifying the pressure on the exchange market. Finally, other variables

[14] Full results can be found in Appendix A.1

[15] For cluster 2, **tradeExposureEU15.gdp_0006** and **imp_0206** are marginally significant with the posterior probability close to 0.5.

that have been previously flagged as important determinants of EMP, such as imbalances in the current account, international reserves or real exchange rate misalignment—although having their expected signs—do not appear robust in our data.

To check the consistency and robustness for the results in Table 3, we consider an alternative EMP measure, $EMPu_{max.0006}$, as the response variable. This variable is the maximum EMP normalized to the pre-crisis EMP average. As shown in Table 4, two striking observations can be made. First, while the rankings are generally similar, there are more significant covariates with the PIP above 0.5, particularly in cluster 1.[16] For example, the average pre-crisis inflation rate, **infl_0006**, is ranked 10 with the PIP of 0.611, but it only receives a moderate support when the maximum EMP is considered. This variable is also one of a few robust leading indicators found in Feldkircher et al. (2014). Our result also support the positive role of the price stability in containing the external market pressures as in Feldkircher et al. (2014). Second, the average pre-crisis EMP, **EMP_0006**, is robustly important and negatively correlated with the EMP during the crisis. This result is also consistent with Feldkircher et al. (2014). Overall, the results from Table 4 corroborate the findings of Table 3 even when a different measure of EMP is considered.

The robust FMR model allows us to identify outliers based on the posterior estimate of $E(\omega|y)$ shown in Figure 4. An observation is considered as a potential outlier when its corresponding estimate $E(\omega|y)$ is greater than 2.5, which implies its variation is 2.5 times larger than the average level across all the observations in the data set. The countries recognized as outliers include China, Mauritania, Seychelles, Venezuela, and the U. S. It is interesting to note that four out of five outlying countries are emerging/developing markets which include the severely affected countries suffered from the abrupt declines in commodity

[16] The list includes **EMP_0006**, **infl_0006**, **openness_0206**, **kof_persCont_06**, **merchTrade.gdp_0006**, **imp_0206**, **dGap_0006Exo**, **exp_0206**, **tradeExp.US.gdp_0006**, and **dom.credit_06**.

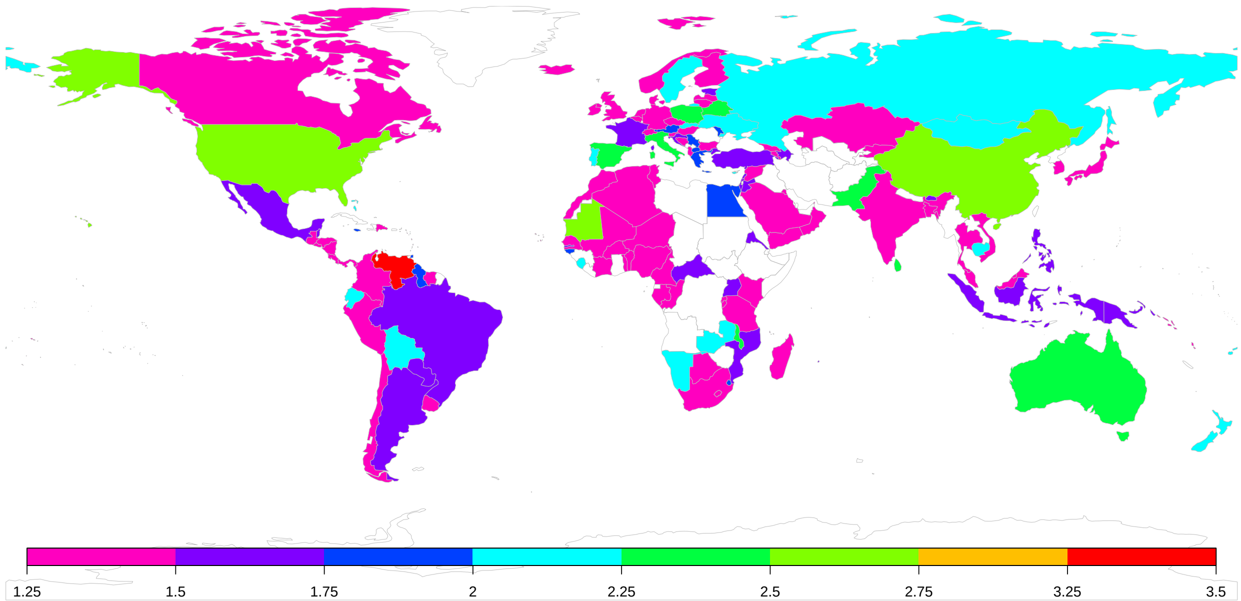

Figure 4: Countries that have high estimates of ω's.

exports and the least affected country of China with the buffer of international reserves. Finally, the U. S. was the epicenter of the recent global financial crisis.

Table 3: Results of Robust Variable Selection for $EMPu_{max}$

		Cluster 1			Cluster 2	
Rank	Variable	PM	PIP	Variable	PM	PIP
1	chg_rgdpcap0006	0.066	0.881	chg_rgdpcap0006	0.131	0.727
2	kof_poltGlob_06	0.083	0.812	openness_0206	0.174	0.641
3	dGap_0006	0.069	0.545	merchTrade.gdp_0006	0.115	0.598
4	money.gdp_06	-0.033	0.517	kof_infFlows_06	0.094	0.570
5	kof_infFlows_06	0.044	0.504	tradeExposureEU15_0006	0.096	0.561
6	dGap_0006Exo	0.055	0.486	kof_poltGlob_06	0.042	0.529
7	kof_overallGlob_06	0.034	0.477	kof_overallGlob_06	0.055	0.527
8	infl_0006	0.139	0.412	dom.credit_06	-0.011	0.523
9	kof_persCont_06	0.037	0.405	money.gdp_06	0.004	0.522
10	dom.credit_06	-0.022	0.399	kof_persCont_06	0.079	0.512
11	outputGap_06Exo	0.111	0.389	adv.claims.gdp_06	0.068	0.507
12	openness_0206	0.008	0.380	petrol.to.Exp_0006	0.203	0.507
13	invRate.gdp_0006	0.084	0.376	dGap_0006Exo	0.108	0.502
14	merchTrade.gdp_0006	-0.009	0.374	ext.debt.exp_06	0.002	0.496
15	imp_0206	0.028	0.358	tradeExposureEU15.gdp_0006	0.139	0.495
16	exp_0206	-0.043	0.348	imp_0206	0.086	0.494
17	ext.debt.exp_06	0.001	0.325	ext.debt.gdp_06	0.004	0.492
18	trade.balance_0206	-0.053	0.316	int.res.ext.debt_06	0.031	0.470
19	int.res.gdp_06	-0.051	0.310	genGovDebt.gdp_06	0.067	0.465
20	kof_cultProx_06	-0.023	0.307	exp_0206	0.091	0.461
...	...	...	...	...	...	...

Note. The table represents a snapshot of the full results and presents the posterior inclusion probability (PIP) of the 20 highest ranked variables across two clusters. PM stands for the posterior mean of the regression coefficient. The estimation of the regression coefficient is based on the Rao-Blackwellized estimators. The degrees of freedom for t-errors assumed to be $v = 5$ in our robust variable selection approach. The variables are ordered by their posterior probabilities. The full name of each variable refers to the Appendix (Table A1).

Table 4: Results of Robust Variable Selection for $EMPu_{max.0006}$

		Cluster 1			Cluster 2	
Rank	Variable	PM	PIP	Variable	PM	PIP
1	kof_poltGlob_06	0.104	0.850	chg_rgdpcap0006	0.187	0.805
2	chg_rgdpcap0006	0.044	0.828	openness_0206	0.206	0.700
3	money.gdp_06	-0.046	0.772	tradeExposureEU15_0006	0.140	0.682
4	dGap_0006	0.092	0.753	merchTrade.gdp_0006	0.139	0.650
5	EMP_0006	-0.558	0.740	kof_infFlows_06	0.100	0.605
6	kof_infFlows_06	0.057	0.708	money.gdp_06	0.061	0.570
7	kof_overallGlob_06	-0.020	0.656	dom.credit_06	-0.012	0.569
8	invRate.gdp_0006	0.196	0.656	kof_poltGlob_06	0.022	0.567
9	outputGap_06Exo	0.204	0.640	kof_overallGlob_06	0.040	0.560
10	infl_0006	0.249	0.611	kof_persCont_06	0.074	0.546
11	openness_0206	0.032	0.611	imp_0206	0.112	0.541
12	kof_persCont_06	0.057	0.597	ext.debt.exp_06	-0.003	0.539
13	merchTrade.gdp_0006	-0.024	0.588	genGovDebt.gdp_06	0.094	0.537
14	imp_0206	0.043	0.583	petrol.to.Exp_0006	0.195	0.528
15	dGap_0006Exo	0.032	0.562	ext.debt.gdp_06	-0.023	0.521
16	exp_0206	-0.017	0.540	tradeExposureEU15.gdp_0006	0.127	0.520
17	tradeExp.US.gdp_0006	-0.147	0.502	dGap_0006Exo	0.064	0.520
18	dom.credit_06	-0.020	0.501	adv.claims.gdp_06	0.011	0.513
19	kof_cultProx_06	-0.036	0.490	int.res.ext.debt_06	0.058	0.501
20	chg.money.gdp_0006	0.026	0.465	exp_0206	0.097	0.501
...	...	...	...	...	...	...

Note. The table represents a snapshot of the full results and presents the posterior inclusion probability (PIP) of the 20 highest ranked variables across two clusters. PM stands for the posterior mean of the regression coefficient. The estimation of the regression coefficient is based on the Rao-Blackwellized estimators. The degrees of freedom for t-errors assumed to be $v = 5$ in our robust variable selection approach. The variables are ordered by their posterior probabilities. The full name of each variable refers to the Appendix (Table A1).

6 Conclusion

In this paper, we consider a robust Bayesian variable selection to the FMR models in the context of the recent global financial crisis. In the process we have demonstrated when the design matrix is not of full rank, an alternative to the g-prior should be used to circumvent the collinearity problem. This work has the potential to have a broad and immediate impact on the variable selection problem when the data is heterogeneously distributed across different subgroups of interest.

Our results are more optimistic than those of Feldkircher et al. (2014) and Rose and Spiegel (2010, 2011, 2012), who investigate which of the previously suggested early warning indicators are effective in explaining the cross-country incidence of the late-2000's crisis. Rose and Spiegel find that equity prices are relatively useful in explaining crisis incidence, but in general their message is skeptical. In comparison to Frankel and Saravelos (2012), who present more optimistic findings concerning the usefulness of early warning indicators (specifically they report that the level of reserves and real appreciation are effective leading indicators), we find different indicators more useful for different types of countries.

In summary, we are confident that Bayesian variable selection approach to a mixture of regression models provides an important application to uncovering underlying structure in covariates, and identify the determinants of external market pressures. We demonstrate the practicality, efficacy and feasibility of a general Bayesian solution to the variable selection problem in mixture regression models. We also expect that the Bayesian framework can complement the growing empirical literature of early warning systems of crisis events. A possible extension of this work would be to relax the assumption of the fixed number of clusters, that is, assuming M is unknown. A starting point is to adopt a hierarchical Bayesian nonparametric mixture model to estimate M based on posterior probability (Yau and Holmes, 2011). Extensions to the subpopulation distribution, other than the normal, for inference involving mixed data types would be a promising direction for future research.

Appendix

A Posterior distribution and full conditionals

In this section, we provide the details of derivation of full conditional distribution of each parameter with the sampling and prior distributions specified in Section 3. The joint posterior distribution is derived as follows. For notation convenience, we set $\theta = (\theta_1, \ldots, \theta_M)$, $\theta_m = (\beta_m, \sigma_m^2, \rho_m, \omega_m, r_m)$ with $\beta_m = (\beta_{m1}, \ldots, \beta_{mp})$, $\omega_m = (\omega_{m1}, \ldots, \omega_{mn_i})$, $r = (r_{m1}, \ldots, r_{mp})$, G_m contains the members in component m, and y_m is a vector consisting of observations in component m, and x_m is the corresponding design matrix. The complete likelihood of the mixture regression model is given by

$$\ell(y, z|\theta) = \prod_{i=1}^{n} \rho_{z_i} f(y_i|\theta_{z_i}) = \prod_{m=1}^{M} \rho_m^{n_m} \left[\prod_{i \in G_m} f(y_i|\theta_{z_i}) \right] .$$

Combining the likelihood and the priors $\pi(\theta)$, we have the posterior distribution as follows

$$p(\theta, z|y) \propto \prod_{m=1}^{M} \rho_m^{n_m} \left[\prod_{i \in G_m} f(y_i|\theta_{z_i}) \right] \pi\left(\theta\right) .$$

The explicit representation of posterior distribution is

$$
\begin{aligned}
p(\theta, z|y) &\propto p(y, z|\beta, \sigma^2, r, \omega, \rho)p(\beta|r, \tau^2)p(\sigma^2)p(\tau^2)p(\omega)p(\rho) \\
&\propto \prod_{m=1}^{M} \rho_m^{n_m} \left(\prod_{i\in G_m} \left(\frac{1}{\sigma_m^2 \omega_i} \right)^{1/2} \right) \exp\left\{ -\frac{(y_m - X_m(r_m)\beta_m(r_m))' \, \Omega_m^{-1} \, (y_m - X_m(r_m)\beta_m(r_m))}{2\sigma_m^2} \right\} \\
&\times \prod_{m=1}^{M} \exp\left\{ -\frac{\beta_m'(r_m)\Lambda_m^{-1}\beta_m(r_m)}{2} \right\} \\
&\times \prod_{m=1}^{M} \left(\frac{1}{\sigma_m^2} \right)^{a_{m_0}/2+1} \exp\left\{ -\frac{b_{m_0}}{2\sigma_m^2} \right\} \\
&\times \prod_{m=1}^{M} \prod_{\{j:r_{mj}\neq 0\}} \left(\frac{1}{\tau_{mj}^2} \right)^{a_{\tau_{mj_0}}/2+1} \exp\left\{ -\frac{b_{\tau_{mj_0}}}{2\tau_{mj}^2} \right\} \\
&\times \prod_{m=1}^{M} \rho_m^{\alpha_m - 1} \\
&\times \prod_{i=1}^{n} \left(\frac{1}{\omega_i} \right)^{a_{\omega_{mj_0}}/2+1} \exp\left\{ -\frac{b_{\omega_{mj_0}}}{2\omega_i} \right\} \\
&\times \prod_{m=1}^{M} \prod_{j=1}^{p} (d_{m,j})^{r_{m,j}} (1 - d_{m,j})^{1-r_{m,j}},
\end{aligned}
$$

where $n_m = \#\{i \in G_m\}$, the number of members in component m, Ω_m is a diagonal matrix of components, ω_i corresponding to i in component m, and Λ is also a diagonal matrix of components τ_j^2 when $r_{mj} \neq 0$ in component m.

The posterior quantities of interest are the probability of a variable included in the model and its expected estimate of regression coefficient, $p(r_{mj} = 1|y)$ and $E(\beta_{mj}|y)$, respectively. These quantities are analytically intractable and must be approximated with Monte Carlo methods. We will describe a particular MCMC method in the subsequent section. A naïve approach would be to construct an MCMC sampler having the full posterior $p(\theta, z|y)$ as the invariant density. Next, we give the conditional probability of each parameter. The parameters in each component are then updated individually using a Gibbs sampler (where available), or a Metropolis-Hastings sampling algorithm. For ease of notation, we drop all required parameters in each conditional distribution.

1. The conditional probability of latent variable z_i is

$$p(z_i = m|y) \propto \rho_m \phi(X_i(r_m)\beta_m(r_m), \omega_i \sigma_m^2),$$

   where $\phi(\mu_{z_m}, \sigma_{z_m}^2)$ stands for the normal density function with mean μ_{z_m} and variance $\sigma_{z_m}^2$.

2. The conditional distribution of ρ follows a Dirichlet distribution given by

$$\rho \sim \text{Dirichlet}(n_1 + \alpha_1, \ldots, n_m + \alpha_m).$$

3. The conditional distribution of σ_m^2 is

$$\begin{aligned} p(\sigma_m^2|y) \propto & \left(\frac{1}{\sigma_m^2}\right)^{n_m/2} \exp\left\{-\frac{(y_m - X_m(r_m)\beta_m(r_m))' \, \Omega_m^{-1} \, (y_m - X_m(r_m)\beta_m(r_m))}{2\sigma_m^2}\right\} \\ & \times \left(\frac{1}{\sigma_m^2}\right)^{a_{m_0}/2+1} \exp\left\{-\frac{b_{m_0}}{2\sigma_m^2}\right\} \end{aligned}$$

   that is, σ_m^2 has an inverse Gamma distribution given by

$$\sigma_m^2 \sim IG\left(\frac{a_m}{2}, \frac{b_m}{2}\right),$$

where

$$
\begin{aligned}
a_m &= n_m + a_{m_0} \\
b_m &= (y_m - X_m(r_m)\beta_m(r_m))' \, \Omega_m^{-1} \, (y_m - X_m(r_m)\beta_m(r_m)) + b_{m_0}.
\end{aligned}
$$

4. The conditional distribution of $\beta_{mj}(r_{mj})$ when $r_{mj} \neq 0$ is

$$
\begin{aligned}
p(\beta_m(r_m)|y) &\propto \exp\left\{-\frac{(y_m - X_m(r_m)\beta_m'(r_m))\,\Omega_m^{-1}\,(y_m - X_m(r_m)\beta_m(r_m))}{2\sigma_m^2} - \frac{\beta_m'(r_m)\Lambda_m^{-1}\beta_m(r_m)}{2}\right\} \\
&\propto \exp\left\{-\frac{\beta_m'(r_m)\left[X_m'(r_m)\Omega^{-1}X_m(r_m) + \sigma_m^2\Lambda_m^{-1}\right]\beta_m(r_m) - 2y_m'\Omega^{-1}X_m(r_m)\beta_m(r_m)}{2\sigma_m^2}\right\} \\
&\propto \exp\left\{-\frac{1}{2}(\beta_m(r_m) - \mu_m)'\Sigma_m^{-1}(\beta_m(r_m) - \mu_m)\right\},
\end{aligned}
$$

where $\mu_m = \Sigma_m X_m'(r_m)\Omega_m^{-1}y_m/\sigma_m^2$ and $\Sigma_m^{-1} = \left(X_m'(r_m)\Omega_m^{-1}X_m(r_m) + \sigma_m^2\Lambda_m^{-1}\right)/\sigma_m^2$.

That is,

$$
\beta_m(r_m)|y \sim N(\mu_m, \Sigma_m).
$$

5. The conditional distribution of τ_{mj}^2 is

$$
p(\tau_{mj}^2|y) \propto \exp\left\{-\frac{\beta_{mj}^2(r_{mj})}{2\tau_{mj}^2}\right\}\left(\frac{1}{\tau_{mj}^2}\right)^{a_{\tau_{mj_0}}/2+1} \exp\left\{-\frac{b_{\tau_{mj_0}}}{2\tau_{mj}^2}\right\}.
$$

That is,

$$
\tau_{mj}^2 \sim IG\left(\frac{a_{\tau_{mj_0}} + 1}{2}, \frac{\beta_{mj}^2(r_{mj}) + b_{\tau_{mj_0}}}{2}\right).
$$

6. The conditional distribution of ω_i is, given $i \in G_m$,

$$
p(\omega_i|y) \propto \left(\frac{1}{\omega_i}\right)^{1/2} \exp\left(-\frac{[y_i - x_{im}(r_{mi})\beta_{mj}(r_{mj})]^2}{2\omega_i\sigma_m^2}\right)\left(\frac{1}{\omega_i}\right)^{a_{\omega_{mj_0}}/2+1} \exp\left\{-\frac{b_{\omega_{mj_0}}}{2\omega_i}\right\}
$$

$$\omega_i \sim IG\left(\frac{a_{\omega_{mj0}}}{2}, \frac{\left[y_i - x_{im}(r_{mi})\beta_{mj}(r_{mj})\right]^2/\sigma_m^2 + b_{\omega_{mj0}}}{2}\right).$$

7. The conditional probability of r_{mj} is

$$p(r_{mj} = 1|r_{m,(-j)}, y) = \frac{p(r_{m,j} = 1|r_{m,(-j)}, y)}{p(r_{mj} = 1|r_{m,(-j)}, y) + p(r_{mj} = 0|r_{m,(-j)}, y)}.$$

where

$$\begin{aligned} p(r_{m,j} = 1|r_{m,(-j)}, y) \propto \exp &\left\{-\frac{(y_m - X_m(r_m)\beta_m(r_m))'\,\Omega_m^{-1}\,(y_m - X_m(r_m)\beta_m(r_m))}{2\sigma_m^2}\right\} \\ &\times \exp\left\{-\frac{\beta_m'(r_m)\Lambda_m^{-1}\beta_m(r_m)}{2}\right\} \times \left(\frac{1}{\tau_{mj}^2}\right)^{a_{\tau_{mj0}}/2} \exp\left\{-\frac{b_{\tau_{mj0}}}{2\tau_{mj}^2}\right\} \\ &\times \prod_{j=1}^{p} (d_{m,j})^{r_{m,j}}(1 - d_{m,j})^{1-r_{m,j}}, \end{aligned}$$

and $r_{m,(-j)}$ denotes a vector of r_m excluding r_{mj}.

A.1 Tables

Table A1: Variable Description for Cross-Country Exchange Market Pressures
(Variables are measured the average over 2000–2006 unless stated otherwise)

Short Name	Variable
exchange market pressure indicators	
EMPu_max	maximum over 2007Q3–2011Q4 period
EMPu_max.0006	distance between maximum during crisis and average EMP
EMPu_Ptt	peak to through measure
GDP and investment rate	
rgdpcap_06	2006 GDP per capita in PPP
chg_rgdpcap0006	Percentage change in GDP per capita in PPP
real.gdp.gr_0006	Average annual growth rate of real GDP
invRate.gdp_0006	Investment rate in % of GDP
Trade and trade composition	
exp_0206	Exports of goods in % of GDP
imp_0206	Imports of goods in % of GDP
openness_0206	Exports and imports of goods in % of GDP
trade.balance_0206	Trade balance in % of GDP
merchTrade.gdp_0006	Merchandise trade in % of GDP
manuf.to.totExp_0006	Exports of manufactured goods in % of total exports
petrol.to.Exp_0006	Exports of petroleum, petroleum products and related materials in % of total exports
food.to.Exp_0006	Exports of food and live animals in % of total exports
Current account and savings	
gross.savings_06	Gross savings in % of GDP, 2006
ca.gdp_0006	Current account in % of GDP
Money and inflation	
infl_0006	Inflation
money.gdp_06	Money and quasi money (M2) in % of GDP, 2006
chg.money.gdp_0006	Percentage change in money and quasi money (M2) in % of GDP
Credit and interest rate	
dom.credit_06	Domestic credit provided by banking sector in % of GDP, 2006
chg.dom.credit_0006	Domestic credit provided by banking sector in % of GDP, percentage change 2000–2006
creditInfIndex_06	Credit depth of information index from 0 (low) to 6 (high)
depRate_06	Deposit rate in % per annum, 2006
Institutional quality	
legRightsIndex_06	Strength of legal rights index from 0 (weak) to 10 (strong)
cpi_corruption_06	CPI (Transparency International's Corruption Perceptions Index)
Debt and external debt	
genGovDebt.gdp_06	General government debt in % of GDP, 2006
genGovBal.gdp_0006	General government budget balance in % of GDP, 2006
ext.debt.gdp_06	External debt in % of GDP, 2006
ext.debt.exp_06	External debt in % of total exports, 2006
adv.claims.gdp_06	Claims of foreign banks (advanced countries) in % of GDP, 2006
Reserves	
int.res.gdp_06	International reserves (excl. gold) in % of GDP, 2006
int.res.ext.debt_06	International reserves (excl. gold) in % of external debt, 2006
Capital flows	
net.fdi.infl_0006	Net FDI inflows in % of GDP
Trade exposure	
tradeExposureUS_0206	Goods imports from and exports to the U.S.A. in % of total exports
tradeExp.US.gdp_0006	Goods imports from and exports to the U.S.A. in % of GDP
tradeExposureEU15.gdp_0006	Goods imports from and exports to the EU-15 in % of GDP
tradeExposureEU15_ 0006	Goods imports from and exports to the EU-15 in % of total exports
Population and unemployment	

Continued on next page

Table A1 – *Continued from previous page*

Short Name	Variable
unempl_06	Unemployment rate, 2006
pop_06	Population in millions
pop.gr_0006	Population growth, percentage change 2000–2006
Monetary regime	
Floater	Dummy variable for countries with no exchange rate anchor
Exchange rate misalignment and output gap	
emp_chg_0006	Exchange market pressure index covering changes in the nominal exchange rate and changes in international reserves, in %, 2006
reerm_06	Measure for overvaluation of the real exchange rate, in %, 2006
dGap_0006	
outputGap_0006Exo	Deviation from trend output in % in 2000–2006
outputGap_06Exo	Deviation from trend output in % in 2006
dGap_0006Exo	Ratio of how often a country was above trend growth in 2000–2006
EMP_0006	Exchange market pressure average
Oil production	
oilExp	Dummy variable for oil exporting countries
oilProd	Total oil produced per day in % of total worldwide oil production in 2008.
Globalization indicators	
kof_persCont_06	KOF Globalization Index, personal contact, 2006
kof_infFlows_06	KOF Globalization Index, information flows, 2006
kof_cultProx_06	KOF Globalization Index, cultural proximity, 2006
kof_poltGlob_06	KOF Political Globalization Index, 2006
kof_overallGlob_06	KOF Overall Globalization Index, 2006
Trilemma indicators	
monInd_06	Monetary independence index
er.stab_06	Exchange rate stability index
FinOpenn_06	Financial Openness Index (Chinn-Ito index)
Country dummies	
adv	Dummy variable for advanced countries.
euroAdopt	Dummy variable for countries that adopted the euro in 2000–2011.

Note. The original source of this table is from Table A2 in Feldkircher et al. (2014).

Table A2: Ranking of Variables across Two Clusters for $EMPu_{max}$

	$v = 5$				$v = 25$				$v = 100$			
	Cluster 1		**Cluster 2**		**Cluster 1**		**Cluster 2**		**Cluster 1**		**Cluster 2**	
Rank	Variable	PIP	Variable	PIP	Variable	PIP	Variable	PIP	Variable	PIP	Variable	PIP
1	chg_rgdpcap0006	0.881	chg_rgdpcap0006	0.727	chg_rgdpcap0006	0.847	chg_rgdpcap0006	0.699	chg_rgdpcap0006	0.844	chg_rgdpcap0006	0.697
2	kof_poltGlob_06	0.812	openness_0206	0.641	kof_poltGlob_06	0.775	openness_0206	0.641	kof_poltGlob_06	0.768	openness_0206	0.639
3	dGap_0006	0.545	merchTrade.gdp_0006	0.598	dGap_0006	0.594	merchTrade.gdp_0006	0.596	dGap_0006	0.595	merchTrade.gdp_0006	0.602
4	money.gdp_06	0.517	kof_infFlows_06	0.570	kof_infFlows_06	0.533	tradeExposureEU15_0006	0.577	kof_infFlows_06	0.539	tradeExposureEU15_0006	0.576
5	kof_infFlows_06	0.504	tradeExposureEU15_0006	0.561	kof_overallGlob_06	0.499	kof_infFlows_06	0.567	kof_overallGlob_06	0.505	petrol.to.Exp_0006	0.568
6	dGap_0006Exo	0.486	kof_poltGlob_06	0.529	money.gdp_06	0.495	petrol.to.Exp_0006	0.554	money.gdp_06	0.495	kof_infFlows_06	0.563
7	kof_overallGlob_06	0.477	kof_overallGlob_06	0.527	dom.credit_06	0.457	kof_persCont_06	0.518	dom.credit_06	0.466	kof_persCont_06	0.523
8	infl_0006	0.412	dom.credit_06	0.523	kof_persCont_06	0.449	kof_overallGlob_06	0.514	kof_persCont_06	0.459	kof_overallGlob_06	0.512
9	kof_persCont_06	0.405	money.gdp_06	0.522	dGap_0006Exo	0.444	kof_poltGlob_06	0.508	outputGap_06Exo	0.438	dom.credit_06	0.507
10	dom.credit_06	0.399	kof_persCont_06	0.512	outputGap_06Exo	0.434	dom.credit_06	0.507	dGap_0006Exo	0.436	money.gdp_06	0.504
11	outputGap_06Exo	0.389	adv.claims.gdp_06	0.507	infl_0006	0.432	money.gdp_06	0.506	infl_0006	0.433	kof_poltGlob_06	0.500
12	openness_0206	0.380	petrol.to.Exp_0006	0.507	invRate.gdp_0006	0.387	dGap_0006Exo	0.500	invRate.gdp_0006	0.385	dGap_0006Exo	0.496
13	invRate.gdp_0006	0.376	dGap_0006Exo	0.502	openness_0206	0.375	imp_0206	0.494	openness_0206	0.374	tradeExposureEU15.gdp_0006	0.496
14	merchTrade.gdp_0006	0.374	ext.debt.exp_06	0.496	imp_0206	0.369	tradeExposureEU15.gdp_0006	0.491	imp_0206	0.369	imp_0206	0.494
15	imp_0206	0.358	tradeExposureEU15.gdp_0006	0.495	merchTrade.gdp_0006	0.356	adv.claims.gdp_06	0.490	merchTrade.gdp_0006	0.360	adv.claims.gdp_06	0.487
16	exp_0206	0.348	imp_0206	0.494	exp_0206	0.356	genGovDebt.gdp_06	0.476	exp_0206	0.355	genGovDebt.gdp_06	0.479
17	ext.debt.exp_06	0.325	ext.debt.gdp_06	0.492	trade.balance_0206	0.339	exp_0206	0.465	trade.balance_0206	0.341	exp_0206	0.462
18	trade.balance_0206	0.316	int.res.ext.debt_06	0.470	int.res.gdp_06	0.323	ext.debt.exp_06	0.459	int.res.gdp_06	0.323	ext.debt.exp_06	0.457
19	int.res.gdp_06	0.310	genGovDebt.gdp_06	0.465	kof_cultProx_06	0.300	int.res.ext.debt_06	0.458	kof_cultProx_06	0.302	int.res.ext.debt_06	0.456
20	kof_cultProx_06	0.307	exp_0206	0.461	gross.savings_06	0.296	ext.debt.gdp_06	0.458	gross.savings_06	0.296	ext.debt.gdp_06	0.450
21	tradeExposureEU15_0006	0.306	kof_cultProx_06	0.456	tradeExp.US.gdp_0006	0.288	kof_cultProx_06	0.446	tradeExp.US.gdp_0006	0.290	food.to.Exp_0006	0.444
22	gross.savings_06	0.305	dGap_0006	0.437	tradeExposureEU15_0006	0.283	food.to.Exp_0006	0.439	tradeExposureEU15_0006	0.278	kof_cultProx_06	0.442
23	pop.gr_0006	0.296	food.to.Exp_0006	0.421	ext.debt.exp_06	0.281	dGap_0006	0.434	manuf.to.totExp_0006	0.277	dGap_0006	0.434
24	adv.claims.gdp_06	0.284	invRate.gdp_0006	0.419	chg.dom.credit_0006	0.280	invRate.gdp_0006	0.423	chg.dom.credit_0006	0.276	invRate.gdp_0006	0.423
25	chg.dom.credit_0006	0.283	gross.savings_06	0.410	pop.gr_0006	0.276	gross.savings_06	0.415	ext.debt.exp_06	0.275	gross.savings_06	0.415
26	tradeExp.US.gdp_0006	0.283	manuf.to.totExp_0006	0.407	adv.claims.gdp_06	0.273	reerm_06	0.408	adv.claims.gdp_06	0.272	reerm_06	0.408
27	chg.money.gdp_0006	0.263	reerm_06	0.405	manuf.to.totExp_0006	0.270	int.res.gdp_06	0.407	pop.gr_0006	0.270	int.res.gdp_06	0.408
28	ext.debt.gdp_06	0.260	int.res.gdp_06	0.402	ext.debt.gdp_06	0.245	trade.balance_0206	0.403	EMP_0006	0.246	trade.balance_0206	0.404
29	genGovDebt.gdp_06	0.258	outputGap_06Exo	0.400	chg.money.gdp_0006	0.241	outputGap_06Exo	0.402	unempl_06	0.243	outputGap_06Exo	0.403
30	manuf.to.totExp_0006	0.252	trade.balance_0206	0.398	unempl_06	0.240	tradeExposureUS_0206	0.401	chg.money.gdp_0006	0.241	tradeExposureUS_0206	0.403
31	reerm_06	0.246	tradeExposureUS_0206	0.395	EMP_0006	0.240	manuf.to.totExp_0006	0.399	depRate_06	0.241	infl_0006	0.398
32	depRate_06	0.231	infl_0006	0.394	depRate_06	0.239	infl_0006	0.398	ext.debt.gdp_06	0.241	manuf.to.totExp_0006	0.397
33	tradeExposureEU15.gdp_0006	0.230	chg.money.gdp_0006	0.391	genGovDebt.gdp_06	0.235	rgdpcap_06	0.395	genGovDebt.gdp_06	0.232	rgdpcap_06	0.396
34	unempl_06	0.226	chg.dom.credit_0006	0.386	reerm_06	0.232	pop.gr_0006	0.393	reerm_06	0.230	tradeExp.US.gdp_0006	0.395
35	EMP_0006	0.221	rgdpcap_06	0.385	tradeExposureEU15.gdp_0006	0.227	tradeExp.US.gdp_0006	0.393	ca.gdp_0006	0.229	pop.gr_0006	0.393
36	ca.gdp_0006	0.219	unempl_06	0.384	ca.gdp_0006	0.227	net.fdi.infl_0006	0.392	rgdpcap_06	0.228	net.fdi.infl_0006	0.393
37	rgdpcap_06	0.219	tradeExp.US.gdp_0006	0.383	rgdpcap_06	0.227	unempl_06	0.392	tradeExposureEU15.gdp_0006	0.226	unempl_06	0.392
38	food.to.Exp_0006	0.217	pop.gr_0006	0.383	food.to.Exp_0006	0.221	legRightsIndex_06	0.391	food.to.Exp_0006	0.220	legRightsIndex_06	0.392
39	tradeExposureUS_0206	0.210	EMP_0006	0.381	legRightsIndex_06	0.215	depRate_06	0.391	legRightsIndex_06	0.216	depRate_06	0.391
40	legRightsIndex_06	0.206	net.fdi.infl_0006	0.381	tradeExposureUS_0206	0.210	creditInfIndex_06	0.390	cpi_corruption_06	0.210	ca.gdp_0006	0.391
41	net.fdi.infl_0006	0.203	ca.gdp_0006	0.381	cpi_corruption_06	0.209	ca.gdp_0006	0.390	tradeExposureUS_0206	0.210	genGovBal.gdp_0006	0.391
42	real.gdp.gr_0006	0.200	legRightsIndex_06	0.380	real.gdp.gr_0006	0.209	real.gdp.gr_0006	0.390	real.gdp.gr_0006	0.209	creditInfIndex_06	0.391
43	cpi_corruption_06	0.200	depRate_06	0.380	outputGap_0006Exo	0.208	genGovBal.gdp_0006	0.390	outputGap_0006Exo	0.209	cpi_corruption_06	0.390
44	outputGap_0006Exo	0.198	genGovBal.gdp_0006	0.379	net.fdi.infl_0006	0.208	EMP_0006	0.389	net.fdi.infl_0006	0.207	real.gdp.gr_0006	0.390
45	petrol.to.Exp_0006	0.198	cpi_corruption_06	0.378	creditInfIndex_06	0.204	cpi_corruption_06	0.389	creditInfIndex_06	0.205	EMP_0006	0.390
46	genGovBal.gdp_0006	0.196	creditInfIndex_06	0.377	genGovBal.gdp_0006	0.203	chg.money.gdp_0006	0.389	genGovBal.gdp_0006	0.204	outputGap_0006Exo	0.389
47	creditInfIndex_06	0.196	real.gdp.gr_0006	0.377	pop_06	0.201	outputGap_0006Exo	0.388	pop_06	0.203	FinOpenn_06	0.389
48	int.res.ext.debt_06	0.196	pop_06	0.376	int.res.ext.debt_06	0.201	pop_06	0.388	int.res.ext.debt_06	0.201	euroAdopt	0.389
49	pop_06	0.193	outputGap_0006Exo	0.376	Floater	0.199	FinOpenn_06	0.387	Floater	0.200	pop_06	0.389
50	oilProd	0.190	oilProd	0.376	oilProd	0.199	er.stab_06	0.387	FinOpenn_06	0.200	oilProd	0.389
51	FinOpenn_06	0.190	monInd_06	0.375	FinOpenn_06	0.199	euroAdopt	0.387	er.stab_06	0.200	oilExp	0.388
52	Floater	0.190	adv	0.375	monInd_06	0.199	emp_chg_0006	0.387	oilExp	0.200	emp_chg_0006	0.388
53	monInd_06	0.190	er.stab_06	0.375	adv	0.199	oilExp	0.387	oilProd	0.200	adv	0.388
54	oilExp	0.190	euroAdopt	0.375	euroAdopt	0.199	oilProd	0.387	adv	0.200	Floater	0.388
55	adv	0.190	FinOpenn_06	0.375	oilExp	0.199	Floater	0.387	monInd_06	0.200	monInd_06	0.388
56	er.stab_06	0.190	emp_chg_0006	0.374	emp_chg_0006	0.198	adv	0.386	emp_chg_0006	0.199	er.stab_06	0.388
57	euroAdopt	0.190	oilExp	0.374	er.stab_06	0.198	monInd_06	0.386	euroAdopt	0.199	chg.money.gdp_0006	0.387
58	emp_chg_0006	0.189	Floater	0.374	petrol.to.Exp_0006	0.198	chg.dom.credit_0006	0.384	petrol.to.Exp_0006	0.198	chg.dom.credit_0006	0.382

Note. PIP stands for the posterior inclusion probability of each variable included in the model. v denotes the fixed degrees of freedom for t-errors in our robust variable selection approach. The variables are ordered by the posterior probabilities. The full name of each variable refers to Table A1.

Table A3: Ranking of Variables across Two Clusters for $EMPumax.0006$

	$v = 5$				$v = 25$				$v = 100$			
	Cluster 1		Cluster 2		Cluster 1		Cluster 2		Cluster 1		Cluster 2	
Rank	Variable	PIP	Variable	PIP	Variable	PIP	Variable	PIP	Variable	PIP	Variable	PIP
1	kof_poltGlob_06	0.850	chg_rgdpcap0006	0.805	kof_poltGlob_06	0.816	chg_rgdpcap0006	0.790	kof_poltGlob_06	0.812	chg_rgdpcap0006	0.784
2	chg_rgdpcap0006	0.828	openness_0206	0.700	chg_rgdpcap0006	0.810	openness_0206	0.695	chg_rgdpcap0006	0.808	openness_0206	0.691
3	money.gdp_06	0.772	tradeExposureEU15_0006	0.682	EMP_0006	0.786	tradeExposureEU15_0006	0.664	EMP_0006	0.800	tradeExposureEU15_0006	0.663
4	dGap_0006	0.753	merchTrade.gdp_0006	0.650	dGap_0006	0.753	merchTrade.gdp_0006	0.639	dGap_0006	0.751	merchTrade.gdp_0006	0.638
5	EMP_0006	0.740	kof_infFlows_06	0.605	money.gdp_06	0.737	kof_infFlows_06	0.588	kof_infFlows_06	0.733	kof_infFlows_06	0.587
6	kof_infFlows_06	0.708	money.gdp_06	0.570	kof_infFlows_06	0.732	petrol.to.Exp_0006	0.555	money.gdp_06	0.733	petrol.to.Exp_0006	0.557
7	kof_overallGlob_06	0.656	dom.credit_06	0.569	kof_overallGlob_06	0.670	money.gdp_06	0.553	kof_overallGlob_06	0.676	money.gdp_06	0.548
8	invRate.gdp_0006	0.656	kof_poltGlob_06	0.567	infl_0006	0.653	kof_poltGlob_06	0.543	infl_0006	0.666	kof_overallGlob_06	0.536
9	outputGap_06Exo	0.640	kof_overallGlob_06	0.560	invRate.gdp_0006	0.653	kof_overallGlob_06	0.540	invRate.gdp_0006	0.657	dom.credit_06	0.535
10	infl_0006	0.611	kof_persCont_06	0.546	outputGap_06Exo	0.640	dom.credit_06	0.540	outputGap_06Exo	0.639	kof_poltGlob_06	0.534
11	openness_0206	0.611	imp_0206	0.541	openness_0206	0.617	kof_persCont_06	0.535	openness_0206	0.627	kof_persCont_06	0.531
12	kof_persCont_06	0.597	ext.debt.exp_06	0.539	kof_persCont_06	0.605	imp_0206	0.532	kof_persCont_06	0.610	imp_0206	0.528
13	merchTrade.gdp_0006	0.588	genGovDebt.gdp_06	0.537	imp_0206	0.591	tradeExposureEU15.gdp_0006	0.515	imp_0206	0.596	tradeExposureEU15.gdp_0006	0.512
14	imp_0206	0.583	petrol.to.Exp_0006	0.528	merchTrade.gdp_0006	0.585	genGovDebt.gdp_06	0.511	merchTrade.gdp_0006	0.589	genGovDebt.gdp_06	0.508
15	dGap_0006Exo	0.562	ext.debt.gdp_06	0.521	exp_0206	0.551	ext.debt.exp_06	0.506	exp_0206	0.556	ext.debt.exp_06	0.502
16	exp_0206	0.540	tradeExposureEU15.gdp_0006	0.520	dGap_0006Exo	0.551	dGap_0006Exo	0.503	dom.credit_06	0.555	dGap_0006Exo	0.500
17	tradeExp.US.gdp_0006	0.502	dGap_0006Exo	0.520	dom.credit_06	0.546	ext.debt.gdp_06	0.493	dGap_0006Exo	0.547	adv.claims.gdp_06	0.489
18	dom.credit_06	0.501	adv.claims.gdp_06	0.513	tradeExp.US.gdp_0006	0.510	adv.claims.gdp_06	0.492	tradeExp.US.gdp_0006	0.511	ext.debt.gdp_06	0.486
19	kof_cultProx_06	0.490	int.res.ext.debt_06	0.501	kof_cultProx_06	0.498	exp_0206	0.490	kof_cultProx_06	0.499	exp_0206	0.486
20	chg.money.gdp_0006	0.465	exp_0206	0.501	gross.savings_06	0.462	int.res.ext.debt_06	0.484	gross.savings_06	0.464	int.res.ext.debt_06	0.478
21	gross.savings_06	0.452	kof_cultProx_06	0.487	chg.money.gdp_0006	0.458	kof_cultProx_06	0.470	int.res.gdp_06	0.462	kof_cultProx_06	0.467
22	trade.balance_0206	0.450	dGap_0006	0.479	int.res.gdp_06	0.456	dGap_0006	0.463	chg.money.gdp_0006	0.460	dGap_0006	0.459
23	pop.gr_0006	0.445	food.to.Exp_0006	0.460	trade.balance_0206	0.454	food.to.Exp_0006	0.459	trade.balance_0206	0.456	food.to.Exp_0006	0.459
24	int.res.gdp_06	0.442	invRate.gdp_0006	0.457	pop.gr_0006	0.434	invRate.gdp_0006	0.448	pop.gr_0006	0.434	invRate.gdp_0006	0.447
25	ext.debt.exp_06	0.429	chg.dom.credit_0006	0.450	adv.claims.gdp_06	0.419	outputGap_06Exo	0.440	adv.claims.gdp_06	0.424	outputGap_06Exo	0.437
26	adv.claims.gdp_06	0.413	outputGap_06Exo	0.447	ext.debt.exp_06	0.410	gross.savings_06	0.435	ext.debt.exp_06	0.408	gross.savings_06	0.433
27	tradeExposureEU15_0006	0.407	gross.savings_06	0.444	tradeExposureEU15_0006	0.407	chg.dom.credit_0006	0.430	tradeExposureEU15_0006	0.406	int.res.gdp_06	0.427
28	ext.debt.gdp_06	0.386	manuf.to.totExp_0006	0.442	rgdpcap_06	0.393	int.res.gdp_06	0.429	rgdpcap_06	0.400	manuf.to.totExp_0006	0.425
29	tradeExposureEU15.gdp_0006	0.386	reerm_06	0.441	tradeExposureUS_0206	0.390	manuf.to.totExp_0006	0.427	tradeExposureUS_0206	0.394	chg.dom.credit_0006	0.424
30	genGovDebt.gdp_06	0.380	int.res.gdp_06	0.436	tradeExposureEU15.gdp_0006	0.390	reerm_06	0.426	tradeExposureEU15.gdp_0006	0.393	reerm_06	0.423
31	rgdpcap_06	0.379	EMP_0006	0.433	ext.debt.gdp_06	0.382	EMP_0006	0.425	manuf.to.totExp_0006	0.384	EMP_0006	0.423
32	tradeExposureUS_0206	0.375	chg.money.gdp_0006	0.429	manuf.to.totExp_0006	0.380	trade.balance_0206	0.422	ext.debt.gdp_06	0.384	trade.balance_0206	0.420
33	manuf.to.totExp_0006	0.368	trade.balance_0206	0.428	unempl_06	0.375	tradeExposureUS_0206	0.420	genGovDebt.gdp_06	0.376	tradeExposureUS_0206	0.418
34	unempl_06	0.367	tradeExposureUS_0206	0.427	genGovDebt.gdp_06	0.374	infl_0006	0.416	unempl_06	0.376	infl_0006	0.415
35	chg.dom.credit_0006	0.361	infl_0006	0.421	legRightsIndex_06	0.371	unempl_06	0.413	legRightsIndex_06	0.375	rgdpcap_06	0.410
36	reerm_06	0.355	unempl_06	0.418	chg.dom.credit_0006	0.370	pop.gr_0006	0.412	chg.dom.credit_0006	0.370	pop.gr_0006	0.410
37	legRightsIndex_06	0.352	pop.gr_0006	0.414	real.gdp.gr_0006	0.353	tradeExp.US.gdp_0006	0.411	real.gdp.gr_0006	0.357	unempl_06	0.410
38	ca.gdp_0006	0.337	tradeExp.US.gdp_0006	0.414	cpi_corruption_06	0.349	rgdpcap_06	0.411	cpi_corruption_06	0.356	tradeExp.US.gdp_0006	0.409
39	real.gdp.gr_0006	0.336	rgdpcap_06	0.413	depRate_06	0.341	net.fdi.infl_0006	0.410	depRate_06	0.344	net.fdi.infl_0006	0.409
40	cpi_corruption_06	0.330	ca.gdp_0006	0.411	reerm_06	0.340	ca.gdp_0006	0.409	creditInfIndex_06	0.342	ca.gdp_0006	0.408
41	food.to.Exp_0006	0.330	net.fdi.infl_0006	0.411	ca.gdp_0006	0.340	depRate_06	0.408	ca.gdp_0006	0.341	depRate_06	0.407
42	net.fdi.infl_0006	0.329	legRightsIndex_06	0.409	net.fdi.infl_0006	0.337	legRightsIndex_06	0.408	net.fdi.infl_0006	0.340	legRightsIndex_06	0.406
43	depRate_06	0.328	depRate_06	0.408	creditInfIndex_06	0.337	chg.money.gdp_0006	0.407	reerm_06	0.338	creditInfIndex_06	0.406
44	petrol.to.Exp_0006	0.327	real.gdp.gr_0006	0.406	food.to.Exp_0006	0.332	genGovBal.gdp_0006	0.406	food.to.Exp_0006	0.335	genGovBal.gdp_0006	0.405
45	creditInfIndex_06	0.321	cpi_corruption_06	0.406	petrol.to.Exp_0006	0.328	creditInfIndex_06	0.406	petrol.to.Exp_0006	0.330	real.gdp.gr_0006	0.404
46	genGovBal.gdp_0006	0.309	genGovBal.gdp_0006	0.406	pop_06	0.324	real.gdp.gr_0006	0.406	pop_06	0.328	cpi_corruption_06	0.404
47	pop_06	0.307	creditInfIndex_06	0.405	outputGap_0006Exo	0.321	cpi_corruption_06	0.405	outputGap_0006Exo	0.324	pop_06	0.404
48	outputGap_0006Exo	0.307	outputGap_0006Exo	0.404	genGovBal.gdp_0006	0.316	pop_06	0.404	genGovBal.gdp_0006	0.320	FinOpenn_06	0.403
49	oilProd	0.298	pop_06	0.404	Floater	0.314	outputGap_0006Exo	0.404	Floater	0.319	oilProd	0.403
50	Floater	0.297	er.stab_06	0.403	monInd_06	0.314	oilProd	0.404	monInd_06	0.317	outputGap_0006Exo	0.403
51	monInd_06	0.297	monInd_06	0.403	oilExp	0.313	monInd_06	0.404	er.stab_06	0.317	er.stab_06	0.403
52	oilExp	0.296	oilExp	0.403	FinOpenn_06	0.313	euroAdopt	0.403	oilExp	0.317	emp_chg_0006	0.403
53	FinOpenn_06	0.296	adv	0.403	emp_chg_0006	0.313	FinOpenn_06	0.403	FinOpenn_06	0.317	oilExp	0.403
54	int.res.ext.debt_06	0.296	FinOpenn_06	0.403	er.stab_06	0.313	er.stab_06	0.403	emp_chg_0006	0.317	chg.money.gdp_0006	0.403
55	er.stab_06	0.295	emp_chg_0006	0.403	adv	0.313	oilExp	0.403	adv	0.317	adv	0.403
56	emp_chg_0006	0.295	euroAdopt	0.403	euroAdopt	0.312	emp_chg_0006	0.403	euroAdopt	0.317	Floater	0.402
57	euroAdopt	0.295	oilProd	0.402	oilProd	0.312	Floater	0.403	oilProd	0.316	monInd_06	0.402
58	adv	0.295	Floater	0.402	int.res.ext.debt_06	0.304	adv	0.402	int.res.ext.debt_06	0.307	euroAdopt	0.402

Note. PIP stands for the posterior inclusion probability of each variable included in the model. v denotes the fixed degrees of freedom for t-errors in our robust variable selection approach. The variables are ordered by the posterior probabilities. The full name of each variable refers to Table A1.

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