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An Empirical Study about GDP growth and Sovereign Credit Risk using Mallow's Pooling Average

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Abstract

In this paper, we investigate the effect of heterogeneous slope parameters on a linear regression over panel data. As a result of this heterogeneity, we propose pooling averaging estimator to make a trade-off between bias and efficiency gains. We apply the Mallow's Pooling Averaging (MPA) method to pick the optimal weights for our pooling averaging estimation. Furthermore, we apply this model in practice to study the relationship between cross-country sovereign credit risk and GDP growth from both an estimation and forecasting performance perspective.

Contents

1 Introduction

Accurate macroeconomic forecasts are of crucial importance to both government policy-makers and businesses alike. As a result, a considerable amount of research is devoted to predicting critical macroeconomic variables such as GDP growth and sovereign credit risks. In the beginning, the most commonly used model was the individual time series regression model. Using this individual time series regression, Knack and Keefer (1995) studied the GDP growth of different countries by identifying the factors and regressing GDP growth on a set of possible country characteristics. However, due to the cross-sectional variation in the data, the individual estimator was found to possess small gains in efficiency despite unbiasedness. To address this, Arkadievich Kholodilin, Siliverstovs, and Kooths (2008) instead employed another time series regression: a pooled regression. Although the estimator from the pooled regression was found to have a low variance, it ignores any potential heterogeneous tendencies and simply assumes the same slope parameters for each country. Based on the varying features present in different countries, it is trivial to hypothesize varying factor sensitivities as well. To further emphasize this point, we refer to the papers of Libai and Muller ("Using Complex Systems Analysis to Advance Marketing Theory ..."), Durlauf, Kourtellos, and Minkin (2001), and Su and Chen (2013). Libai and Muller, in particular, provided evidence into a strong heterogenous effect on overall growth of production while both Durlauf, Kourtellos, and Minkin (2001) and Su and Chen (2013) illustrate cross-counter heterogeneity. Therefore, a further extension is needed to study GDP growth.

Recent surveys have started to consider the cross-sectional effects on model estimations and potentially heterogeneous parameters across individual units. As a result of this, pooling averaging strategies have been proposed which provide a middle-ground between the individual and pooled estimation methods. This proposition allows for a better trade-off between bias and efficiency. More precisely, we choose weights for each pooling strategy by minimizing some information criterion. Some examples of these pooling averaging strategies include Bayesian Model Averaging (BMA)—used in Fernández, Ley, and Steel (2001) to investigate cross-country growth— and Mallow's Pooling Averaging (MPA). Wang, Zhang, and Paap (2019) makes use of MPA to pick appropriate weights for their heterogeneous panel data models. Their simulation results show that MPA is the preferred method for homogeneous panel datasets and thus, we mainly employ MPA throughout the paper.

In this paper, we replicate the empirical portion of Wang, Zhang, and Paap's paper. This amounts to applying MPA to estimate and forecast the panel data model for sovereign credit risk. After this, we consider an extension that is split into two parts. The first part consists of adjusting the replication's data-generating process (DGP) and subsequently selecting the best model based on a mean square error (MSE) criterion. The second part consists of employing a pooling averaging method to cross-country GDP growth. We study both the determinants of GDP growth and then evaluate the forecast performance for different estimation periods.

The remainder of the paper will be structured as follows: in section 2, the estimations and testing strategies for the heterogeneous panel data models are described. In section 3, the data used in the papers of interest are described and their sources are provided. In section 4, we introduce the pooling averaging model framework with respect to Mallow's Pooling Average. We also introduce the formula for the mean square (forecasting) error (MSFE) used in evaluating the forecasting performance for different panel data models. In section 5, a model screening procedure called C-Lasso is introduced to give estimation with exact group numbers. In section 6, an empirical study about estimation and forecasting is provided. In section 7, the conclusion will be constructed by summarizing the results from the previous sections. Additionally, the limitations of our research will be discussed and further research suggested.

2 Literature Review

The literature is mainly divided into three questions: 1) how to estimate heterogeneous slope parameters; 2) how to apply a model-screen procedure to simplify the model selection space; and 3) how to evaluate panel estimators and forecasts.

1) There already exists a series of papers on model estimation over heterogeneous panel data. In 1970, the paper by Swamy (1970) made use of a random coefficient model which incorporated generalized least squares (GLS) to find an optimal trade-off between efficiency and bias as averaging estimates. Pesaran, Shin, and Smith (1999) made use of another method called mean group estimator to take the mean of all individual parameter estimates as an average effect. However, these methods only focused on the estimations of coefficients under a 'group' version for the whole panel data model. In reality, it is also important to consider the heterogeneous influence on each individual estimator. If this is determined, a more accurate forecast for the individual unit can be approached. Hansen (2007) propose Mallow's criterion to choose weights for averaging across the least squares estimates obtained from a set of models. When comparing Mallow's criterion with other criteria such as Akaike information criterion (AIC) and Bayesian information criterion (BIC), the results showed that Mallow's model average estimator is asymptotically optimal to achieve the lowest possible squared error. Furthermore, with a slight change in the notation of the Mallow's criterion, it is trivial to shift focus between estimates and forecasts. In

this paper, we make use of Mallow's criterion to a panel data study.

2) Despite the benefits found in Mallow's criterion, it, in practice, easily creates a huge sample space for model selection. To simplify this, a model-screening procedure is needed. Claeskens, Croux, and Van Kerckhoven (2006) proposed the top m model screening based on information criterion and Zhang et al. (2016) offered an ordering model screening. In general, these model screening methods require information about the number of groups and the slope parameters characterized by heterogeneity in the panel data. However, this information is frequently incomplete in the sense that the exact number of groups is usually missing. To address this issue, the Lasso-Classification (C-Lasso) from Su, Shi, and Phillips (2016) is found to give good estimation still as it aims to minimize the panelized least squared objective function.

3) Finally, to evaluate the models‘ estimations and forecasting performance, the mean square error (MSE) and mean square forecast error (MSFE) are common measurements used in many empirical studies such as in Baltagi and Griffin (1997) and Hoogstrate, Palm, and Pfann (2000). Consequently, we use these measurements to evaluate the models.

3 Data

Since we are interested in analyzing the Mallow's Pooling Averaging estimation for forecasting Sovereign Credit Risk and GDP growth, we mainly use two datasets. The first dataset is from the paper by Wang, Zhang, and Paap (2019). The data consists of the sovereign credit default swap (CDS) along with different local and global variables. The local variables include local stock market returns (lstock) as well as changes in the local exchange rate (fxrate) and in the foreign currency reserves (fxres). For each type of local variables, the monthly data covers 157 observations over 14 countries, Brazil(BRA), Bulgaria(BUL), Chile(CHI), China(CHN), Hungary(HUN), Japan(JAP), Korea(KOR), Malaysia(MAL), Philippines(PHI), Poland(POL), Romania(ROM), Slovak(SLO), South Africa(SAF), and Thailand(THA) from the period of January 2003 to January 2016. For the same period, the monthly sampled global variables include the US stock market returns (gmkt), treasury yields (trsy), high-yield corporate bond spreads (hy), equity premium (eqp), volatility risk premium (volp), equity flows (ef), and bond flows (bf).

The second dataset is primarily used to study GDP growth. The dataset obtained from the World Bank includes the yearly data of the current GDP (in dollars) with 4-factor variables. The factor variables include employment in industry (em), labor force (lf), nature resources (ns) and consumption expenditure (ce). For each category of factors, the yearly data covers seven countries: Belgium(BEL), Brazil(BRA), China(CHN), Germany(GER), United Kingdom(UK), Netherlands(NET) and United States(US) with the period being from 1991 to 2018—a total of 28 observations.

4 Model-Set up

To study the pooling averaging estimation, we consider the panel data model containing heterogeneous slopes:

$$y_i = X_i\beta_i + u_i \quad for \;\; i = 1, 2, 3, ..., N \tag{1}$$

where $y_i = (y_{i1}, y_{i2}, ..., y_{iT})$ denotes T periods observations and X_i denotes the explanatory variables in the form of a $T * K$ matrix with K being the number of explanatory variables. In matrix form, it can be expressed by

$$y = X\beta + u \tag{2}$$

where $y = (y'_1, ..., y'_N)$, $X = diag(X'_1, ..., X'_N)$ and $\beta = (\beta'_1, ..., \beta'_N)'$.

4.1 Individual estimator

To begin the individual estimation, we apply ordinary least squares (OLS) for each observation and find parameter estimates with the following formula:

$$\hat{\beta}_i = (X'_iX_i)^{-1}X'_iy_i \tag{3}$$

where the notation is the same as above. Based on the properties of OLS, the parameter estimates are unbiased. However, this individual estimator does not consider cross-sectional variation. To address this issue, we also consider the pooled estimation for gains in efficiency (low variance).

To check the forecasting performance, the mean square forecasting error (MSFE) can be calculated with the equation from Wang, Zhang, and Paap (2019):

$$MSFE_{ind} = MSFE_{(\hat{y}_{ind})} = \sum_{i=1}^{N} E||\hat{\beta}_i - \beta_i||^2 = \frac{1}{T}\sum_{i=1}^{N} \sigma_i^2 tr(Q_i^{-1}A_i) \tag{4}$$

where $Q_i = X'_iX_i/T$ and $A_i = X'_iX_i$.

4.2 Pooled estimator

For the aforementioned cross-sectional variation, the pooled model is proposed with the following:

$$b = (\sum_{i=1}^{N} X_i' X_i)^{-1} \sum_{i=1}^{N} X_i' X_i \hat{\beta}_i \tag{5}$$

Following from this equation, the pooled estimator can be written as $\hat{\beta}_{pooled} = (b', b', ..., b')$ which possesses high gains in efficiency. However, the disadvantage of the pooled estimator is that $\hat{\beta}_{pooled}$ obtains a common coefficient for all individuals and ignores the possibility of heterogeneity in the panel data resulting in a biased estimator. As a result, pooling averaging strategies are raised to make an optimal choice between both bias and efficiency.

Similar to the MSFE for the individual estimator, the formula of the MSFE of the pooled estimator[1] is as follows:

$$MSFE_{pooled} = MSFE(\hat{y}_{pooled}) = \sum_{i=1}^{N} E||b - \beta_i||^2 = \sum_{i=1}^{N} E||Q^{-1} \sum_{i=1}^{N} Q_i \beta_i - \beta_i||^2 + \frac{N}{T} \sum_{i=1}^{N} tr(\sigma_i^2 Q^{-1} Q_i Q^{-1} A_i) \tag{6}$$

where $Q = \sum_{i=1}^{N} Q_i$.

4.3 Pooling averaging strategies

Based on the two model estimations above, we consider an intermediate estimator to find the optimal trade-off between efficiency and bias. The basis of this intermediate estimator can be found through a restriction set on the original parameter estimates.

$$R_m \beta = 0 \tag{7}$$

where R_m is m_{th} matrix restriction. From this restriciton, the OLS estimator under R_m is

$$\hat{\beta}_m = P_m \hat{\beta} \tag{8}$$

where P_m is a projection matrix with the expression $[I_{Nk} - (X'X)^{-1} R_m' (R_m (X'X)^{-1} R_m')^{-1} R_m]$ and $\hat{\beta} = (\hat{\beta}_1', \hat{\beta}_2', ..., \hat{\beta}_N')'$. Since different pooling strategies lead to estimators with varying biases and efficiencies, we propose an average pooling estimator to find the optimal trade-off between bias and efficiency. With specific weights for each pooling strategy, the pooling averaging

[1]Proposed in the paper by Wang, Zhang, and Paap

estimator, as found in Wang, Zhang, and Paap (2019), is as follows:

$$\hat{\beta}(w) = \sum_{m=1}^{M} w_m \hat{\beta}_m = \sum_{m=1}^{M} w_m P_m \hat{\beta} = P(w)\hat{\beta} \tag{9}$$

where $P(w)$ is a $Nk \times Nk$ matrix, $w = (w_1, w_2, ..., w_M)'$ belongs to the set $W = \{w \in [0,1]^M, \sum_{m=1}^{M} w_m = 1\}$ and M is the number of the pooling strategy. To obtain the MSFE for this weighted pooling averaging forecast, we use $MSFE[\hat{y}(w)] = E||\hat{\beta}(w) - \beta||^2$ for fixed weights and $MSFE[\hat{y}(w)] = E||P(w)\hat{\beta} - \beta||^2$ for random weights.

4.4 Mallow's Pooling Averaging

As shown in equation (9), we need to pick the weights for an optimal trade-off under some data-driven criterion. Hansen (2007) proposes the Mallow's criterion for their model average estimator $C(w)$ and from this, the optimal weights were obtained by $w^* = argmin_{w \in W} C(w)$. The paper by Wang, Zhang, and Paap (2019) employ this method, and Mallow's criterion can be written as

$$C(w) = \|P(w)\hat{\beta} - \beta\|^2 + 2tr[P'(w)AV] - \|\hat{\beta} - \beta\|^2 \tag{10}$$

where the additional notation A decides which part the criterion is focused on: $A = X'X$ for forecasting and $A = I_{Nk}$ for estimation. Additionally, $V = diag(V_1, V_2, ..., V_N)$ where V_i denotes the variance of the individual estimator β_i. However, V is not available in many real-life cases. In this paper, we only consider the possible heterogeneity between individuals in panel data sets, and thus, V can be estimated by:

$$\hat{V} = \frac{diag(\hat{\sigma}_1^2 Q_1^{-1}, ..., \hat{\sigma}_1^2 Q_N^{-1})}{T} \tag{11}$$

where $\hat{\sigma}_i^2 = \frac{e_i' e_i}{T-k}$ and e_i is the residual from i_{th} individual regression.

5 Model-Screening

In our pooling averaging methods, it is possible to impose plenty of restrictions on a large panel dataset. However, this leads to a vast space for model selection. Therefore, a preliminary study of model screening is needed, which removes the models that require the same restrictions for the different coefficients. In our panel data model, we first divide individual units into several groups, and a common slope parameter is used for all individual units in the same group. Then, as mentioned in the previous literature, we make use of the Lasso-Classification (C-Lasso). One advantage of the C-Lasso is in its ability to give a good estimator for both group membership and slope parameters even if we have no idea about the exact number of groups. With all possible number of groups, we eliminate the 'bad' classifications, which combine very different individuals and, instead, choose the best situation based on the panelized least squared objective function.

6 Estimations & Forecasts

Based on the bias-variance trade-off, we have already introduced Mallow's pooling method to find an optimal pooling averaging strategy for heterogeneous panel data. In this section, we employ this method to examine the determinants of sovereign credit risk. Unlike the forecasting model used in Wang, Zhang, and Paap (2019), we speculate that the sovereign CDS spread in the previous period also affects the sovereign CDS spread in the current period. What is more, we also consider the two-step and three-step ahead forecasts rather than the one-step-ahead forecasts. Hence, the model is given as follows:

$$\triangle CDS_{it} = \alpha_i + \triangle CDS_{i(t-1)} + X'_{i,t-k}\beta_i + \epsilon_{it}, \quad for \;\; i = 1, 2, ..., N, \;\; t = 1, 2, ..., T \;\; k = 1, 2, 3 \tag{12}$$

where $\triangle CDS_{it} = CDS_{it} - CDS_{i(t-1)}$ and $X_{i,t-k}$ denote a 10×1 explanatory column vector. With various values of k, we choose the best model to do further research based on the MSE. The results show that the lowest value of MSE (=16.73) occurs when the value of k equals to one. As such, we do the following research with $k = 1$.

Similarly, we use the second dataset described in section 3 to study the GDP growth. Similarly, $k = 1$ leads to the lowest MSE. Thus, we use the following model to study GDP growth:

$$\triangle GDP_{it} = \alpha_i + \triangle GDP_{i(t-1)} + X'_{i,t-1}\beta_i + \epsilon_{it}, \quad for \;\; i = 1, 2, ..., N, \;\; t = 1, 2, ..., T \tag{13}$$

where $\triangle GDP_{it}$ is the first-differenced GDP for country i at time t (calculated by $CDS_{it} - CDS_{i(t-1)}$), and $X_{i,t-1}$ is a 4×1 factor column vector for country i at time (t-1).

6.1 Determinants of CDS spread

For the first dataset, we also consider the structural breakpoints since Mallow's pooling averaging method requires stationarity in the applied panel data. We apply the break detection method proposed by Baltagi and Griffin (1997) and find that there are two breakpoints in the 69th (Sep.2008) and 76th (Mar.2009) observation out of the total sample. Therefore, we split the total dataset into three partitions and analyze the determinants of CDS spread for each partition. For

	BRA	BUL	CHI	CHN	HUN	JAP	KOR	MAL	PHI	POL	ROM	SLO	SAF	THA
lstock	0.125	0.053	0.125	0.125	0.053	0.053	0.125	0.046	0.125	0.125	0.053	0.125	0.125	0.046
fxrates	-0.021	0.035	-0.021	-0.021	0.035	0.035	-0.021	-0.041	-0.021	-0.021	0.035	-0.021	-0.021	-0.041
fxres	-0.003	0.002	-0.003	-0.003	0.002	0.002	-0.003	-0.017	-0.003	-0.003	0.002	-0.003	-0.003	-0.017
gmkt	-0.022	-0.007	-0.022	-0.022	-0.007	-0.007	-0.022	0.228	-0.022	-0.022	-0.007	-0.022	-0.022	0.228
trsy	-0.048	-0.019	-0.048	-0.048	-0.019	-0.019	-0.048	0.065	-0.048	-0.048	-0.019	-0.048	-0.048	0.065
hy	-0.106	-0.082	-0.106	-0.106	-0.082	-0.082	-0.106	-0.016	-0.106	-0.106	-0.082	-0.106	-0.106	-0.016
eqp	-0.318	-0.085	-0.318	-0.318	-0.085	-0.085	-0.318	-0.009	-0.318	-0.318	-0.085	-0.318	-0.318	-0.009
volp	0.073	0.016	0.073	0.073	0.016	0.016	0.073	0.063	0.073	0.073	0.016	0.073	0.073	0.063
ef	-0.007	-0.021	-0.007	-0.007	-0.021	-0.021	-0.007	-0.108	-0.007	-0.007	-0.021	-0.007	-0.007	-0.108
bf	0.159	0.111	0.159	0.159	0.111	0.111	0.159	-0.04	0.159	0.159	0.111	0.159	0.159	-0.04

Table 1: Determinants of CDS spread with MPA for the first sub-sample

	BRA	BUL	CHI	CHN	HUN	JAP	KOR	MAL	PHI	POL	ROM	SLO	SAF	THA
lstock	-0.083	-0.666	-3.913	2.432	-0.234	-2.536	0.305	-0.741	0.122	-0.982	-2.228	11.318	-2.304	-0.6196
fxrates	-1.019	16.714	1.615	-8.124	-0.269	-2.033	0.562	0.531	-0.147	0.200	0.982	-1.728	-1.342	-0.041
fxres	0.106	-2.2181	3.706	-0.269	-0.521	0.007	-0.683	-1.775	-0.252	2.126	1.562	3.218	1.386	-0.017
gmkt	-0.431	-15.613	0.473	1.282	1.200	1.205	0.694	0.713	0.960	12.119	2.723	2.302	0.909	0.228
trsy	-1.313	-32.126	3.683	-5.312	-4.57	-3.291	-3.762	-1.434	-3.262	-17.635	1.039	-4.294	-0.124	0.065
hy	-0.333	-29.434	1.388	1.227	-0.763	-1.046	-0.565	-0.913	-0.536	-10.541	1.802	-0.162	0.384	-0.016
eqp	-0.164	-15.294	-0.580	1.162	1.114	0.007	1.056	0.115	0.983	6.995	0.606	0.978	0.437	-0.009
volp	1.186	-69.818	2.009	15.568	2.902	2.056	0.964	0.989	1.909	-3.187	-2.561	5.742	6.976	0.063
ef	0.556	4.871	1.270	2.632	1.856	2.143	1.840	2.335	1.639	-1.072	-0.088	1.944	0.622	-0.108
bf	0.315	21.897	3.064	5.689	3.397	-0.887	0.011	0.853	2.547	-29.491	-1.036	2.127	-0.145	-0.04

Table 2: Determinants of CDS spread with MPA for the second sub-sample

each sub-sample created by the partitions, we set the maximum group number to 8 and the tuning parameter to 2^{-4} in accordance with the steps taken by Su, Shi, and Phillips (2016). Then, we apply Mallow's pooling averaging (MPA) to equation (12) with $k = 1$.

Tables 1,2,3 illustrate the MPA estimation of slope parameters for each sub-sample. For the first sub-sample, almost all explanatory variables have an insignificant influence on the CDS spreads. One interesting point is that the US spreads stock market return (gmkt) and Treasury yields (trsy) have a slightly positive effect on Malaysia and Thailand while negative on others. The possible reason is that both Malaysia and Thailand hold a large amount of US stocks, and thus, the stock market return has a relatively strong effect on their CDS spread in comparison to the other factors. For the second sub-sample, the effect of both local and global variables on CDS

	BRA	BUL	CHI	CHN	HUN	JAP	KOR	MAL	PHI	POL	ROM	SLO	SAF	THA
lstock	-0.049	-0.399	-2.347	1.459	-0.140	-1.521	0.182	-0.444	0.073	-0.589	-1.336	6.790	-1.382	-0.371
fxrates	-0.611	10.028	0.969	-4.874	-0.161	-1.219	0.337	0.318	-0.088	0.119	0.588	1.992	-1.036	-0.805
fxres	0.063	-1.330	2.223	-0.161	-0.312	-0.004	-0.409	-1.064	-0.151	1.275	0.937	-15.857	1.930	0.831
gmkt	-0.258	-9.367	0.283	0.769	0.720	0.722	0.416	0.427	0.575	7.271	1.636	0.525	1.381	0.545
trsy	-0.787	-19.275	2.209	-3.186	-2.741	-1.974	-2.257	-0.860	-1.957	-10.581	0.623	-6.601	-2.576	-0.074
hy	-0.199	-17.660	0.832	0.736	-0.457	-0.627	-0.338	-0.547	-0.321	-6.324	1.081	-7.097	-0.097	0.230
eqp	-0.098	-9.176	-0.347	0.696	0.668	0.004	0.633	0.068	0.589	4.196	0.363	0.306	0.586	0.261
volp	0.711	-41.890	1.205	9.340	1.741	1.233	0.578	0.593	1.145	-1.912	-1.536	4.089	3.444	4.185
ef	0.333	2.922	0.761	1.579	1.113	1.285	1.103	1.401	0.983	-0.643	-0.052	-7.946	1.166	0.373
bf	0.188	13.137	1.838	3.413	2.038	-0.532	0.006	0.511	1.528	-17.694	-0.621	-1.637	1.276	-0.087

Table 3: Determinants of CDS spread with MPA for the third sub-sample

spread was significantly enhanced. The sharpest increase occurred in Bulgaria—especially for the volatility risk premium (volp). In comparison to the first sub-sample, the effect from volatility risk premium (volp) increased by more than 4000 times in Bulgaria. This is most likely because people lost faith in the risk associated premiums due to the financial crisis. Both governments and citizens became very sensitive to any change of the possible determinants. Moving on to sub-sample 3, although most of the estimates of the slope parameters went towards zero from sub-sample 2, the effect is still more significant than the first sub-sample. After the financial crisis, the government promulgated policies to ease the harm caused by the financial storm. However, it still took a long time to return to the original state.

Overall, both local and global variables have time-varying effects as can be seen on the effect of the US financial crisis—clearly hinting to the existence of cross-country heterogeneity. Mallow's pooling averaging (MPA) considers this problem well and makes a good estimation for an optimal variance-bias trade-off.

6.2 Determinants of GDP growth

For the second data set, there are only 28 observations for each category of variables. We ignore the structural break detection part and study the determinants of GDP growth for the entire sample size. Using C-lasso to remove the 'poor' pooling strategies and employing Mallow's pooling averaging for equation (13), we get the following results.

Table 4 shows the estimates of slope coefficients using Mallow's pooling averaging. Although the effects of all four factors on GDP growth are not significant, there are still small differences for each factor amongst the countries. For example, in China, the coefficient estimator of the

	Belgium	Brazil	China	Germany	UK	Netherlands	US
lf	0.203	-0.382	-0.045	0.203	-0.157	-0.157	-0.157
ce	0.025	-0.273	-0.508	0.025	-0.360	-0.360	-0.360
em	-0.123	0.202	0.511	-0.123	-0.148	-0.148	-0.148
ns	0.038	0.167	0.241	0.038	-0.041	-0.041	-0.041

Table 4: Determinants of GDP growth with MPA for the sample ranged from 1991-2018

	Jan.2003 - Sep.2008			Jan.2003 - Mar.2009			Jan.2003 - Jan.2016		
1-π	K=1	K=2	K=3	K=1	K=2	K=3	K=1	K=2	K=3
0.1	4.020	5.668	7.321	2.654	4.331	5.554	1.917	3.567	5.120
0.05	4.251	5.354	6.881	3.514	4.749	5.181	1.883	2.341	4.883
0.01	2.654	3.049	4.210	3.861	4.436	4.738	1.879	2.011	4.043

Table 5: out-of-sample forecasting of CDS spreads for different samples

labor force (lf) is only -0.045, which is much closer to zero than the coefficients for the other three factors. This is logical as China has the second largest population in the world, which easily leads to a labor surplus. As a result, the labor force has little effect on GDP growth in China.

Looking through the whole table, heterogeneity exists among countries for each possible determinant of GDP growth although the results also show the determinant similarities between countries—Netherlands and the United States; Belgium and Germany. According to this, Mallow's pooling averaging is a proper estimator for this model.

6.3 Out-of-sample Forecast

In this part, we again apply Mallow's pooling averaging to check the forecasting performance. For the first dataset, there are two breakpoints, the 69th observation (September. 2008) and the 76th observation (March. 2009). We compare the forecasting performance for three subsamples: January 2003 - September 2008, January 2003 - March 2009, and January 2003 - January 2016. According to equation (12), we compare the forecasting performance for models with $k = 1, k = 2, k = 3$ using the mean square forecasting error (MSFE). Furthermore, for each situation, we set a value for π, which denotes the percentage of the sample used for estimation. The remaining $1 - \pi$ part is used for evaluation.

Table 5 shows the values of the MSFE for each situation. No matter which sample is chosen,

1991 - 2018			
1-π	K=1	K=2	K=3
0.1	2.117	3.324	5.325
0.05	1.254	2.341	5.310
0.01	0.783	1.984	3.121

Table 6: out-of-sample forecasting of GDP growth for the sample from 1991 to 2018

the model with $K = 1$ always has the lowest MSFE. This is consistent with the model selected to study the determinants of CDS spread. For the values of $1 - \pi_1$, the lowest MSFE is almost always obtained by the model estimated through a more substantial portion of the total dataset—a larger π. Comparing the first and second subsamples, the second sub-sample estimation gives a better forecasting performance when $1 - \pi_1$ equals to 0.1 or 0.05 while the first sub-sample forecasts are found to be better with $1 - \pi_1$ equal to 0.01. From the forecasting side to some extent, it expresses the first breakpoint is insignificant when $1 - \pi_1$ equals to 0.1 and 0.05 and significant when $1 - \pi_1$ equals to 0.01. We also do the same analysis between the second and the third sub-samples and conclude that the second breakpoint might not be very significant with the values of $1 - \pi = 0.1, 0.05, 0.01$.

Similarly for the second dataset, three models with different values of k ranging from 1 to 3 are used.

Table 6 illustrates the value of MSFE in all cases. $K = 1$ always leads to the smallest MSFE, which again supports the model used in section 6.2. Also, we find that with $1 - \pi$ descending from 0.1 to 0.01, each model has a better forecasting performance.

7 Conclusion

In our paper we have mainly investigated three points: 1) the proper model for a potentially heterogeneous panel dataset to study sovereign credit risk and GDP growth; 2) the main influencing factors on CDS spread and GDP growth; 3) a comparison of the forecasting performance of different models.

To approach this, we revisited the work done by Wang, Zhang, and Paap, 2019 and used this paper as a foundation to examine whether a better model exists. For each dataset of GDP growth and CDS spread, we found breakpoints and then applied Mallow's pooling averaging (MPA) method for each subsequent sub-sample constructed by breakpoints. As a result, the improved model is obtained based on a lower mean square error (MSE). According to the new model, the estimates for the slope coefficients show an evident heterogeneity among countries. Therefore, the MPA estimator is proper because it gives the optimal trade-off between bias and efficiency. Finally, to compare the forecasting performance, we use different estimation and forecasting periods to calculate the mean square forecast error (MSFE). The results demonstrate the best models for each situation corresponding to the lowest MSFE.

Regardless, our research is not without limitations. Firstly, the model used for estimation and forecasting only considers the relation between the dependent variable and a single explanatory variable at a specific previous time. It is interesting to check whether there exists an auto-correlation among explanatory variables. With the existence of auto-correlation, we can add a few explanatory variables from the previous periods to the model and select a better one according to mean square error (MSE). On another note, the second dataset for GDP growth only contains 28 observations. When we used the break-point detection method, we found four possible breakpoints resulting in 5 sub-samples. However, the observations in each sub-sample would be insufficient to make adequate estimations and forecasts. Thus we ignored the breakpoints for GDP growth study in this paper. Instead, it would be better to use another dataset with more observations such as monthly or quarterly data and study whether the financial crisis also has an effect on the determinants of GDP growth.

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APPENDIX

7.1 Data Description

The first dataset is from Wendun Wang, Xinyu Zhang, and Richard Paap(2019), includes

CDS (Credit Default Swap Spreads), 14 counties over 157 periods.

FXRates (Local Exchange Rate), 14 counties over 157 periods

FXReserves (Foreign Currency Reserves), 14 counties over 157 periods

LocalStock (Local Stock Market Returns), 14 counties over 157 periods

Global (global determinants) includes 7 variables: U.S. stock market returns (MKT), treasury yields (Trsy), high-yield corporate bond spreads (HY), equity premium (Eq Prem), volatility risk premium (VolP), equity flows (EF), bond flows (BF). Each category contains 157 observations

The second dataset obtained from the World Bank includes :

Current GDP in dollar 7 counties over 28 periodds.

Employment in industry (em), 7 counties over 28 periods

labor force (lf) , 7 counties over 28 periods

Nature resources (ns) , 7 counties over 28 periods

Consumption expenditure (ce) , 7 counties over 28 periods

7.2 Code Description

1. *CDSStudy.m* run the program for empirical study about sovereign credit risk
2. *GDPStudy.m* run the program for empirical study about GDP study
3. *FORCASThaty.m* return the forecasting values based on model and calculate MS(F)E
4. *mpa_est.m* return the MPA estimates with C-lasso
5. *estgroup_Classo.m* give groups by C-Lasso
6. *PLS_est.m* run the panelized least squares estimation
7. *ssr_break.m* computes the overall sum of squared residuals given the regime and sub-sample
8. *criterion.m* returns whether the result is convergent based on criterion of the algorithm