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Does accounting for spatial effects help forecasting the growth of Chinese provinces?

Eric Girardin* Konstantin A. Kholodilin**

Abstract

In this paper, we make multi-step forecasts of the annual growth rates of the real GRP for each of the 31 Chinese provinces simultaneously. Beside the usual panel data models, we use panel models that explicitly account for spatial dependence between the GRP growth rates. In addition, the possibility of spatial effects being different for different groups of provinces (Interior and Coast) is allowed. We find that both pooling and accounting for spatial effects helps substantially improve the forecast performance compared to the benchmark models estimated for each of the provinces separately. It was also shown that effect of accounting for spatial dependence is even more pronounced at longer forecasting horizons (the forecast accuracy gain as measured by the root mean squared forecast error is about 8% at 1-year horizon and exceeds 25% at 13- and 14-year horizon).

Keywords: Chinese provinces; forecasting; dynamic panel model; spatial autocorrelation; group-specific spatial dependence.

JEL classification: C21; C23; C53.

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One family builds the wall, two families enjoy it.

Chinese proverb

1 Introduction

In this paper, we conduct the forecasts of the growth rates of real Gross Regional Product (GRP) of Chinese provinces. The problem of data collection for each region is circumvented by pooling the annual growth rates of GRP into a panel and correspondingly utilizing panel data models for forecasting. The advantages of such a pooling approach for forecasting have been widely demonstrated in a series of articles for diverse data sets such as Baltagi and Griffin (1997); Baltagi et al. (2003) — for gasoline demand, Baltagi et al. (2000) — for cigarette demand, Baltagi et al. (2002) — for electricity and natural gas consumption, Baltagi et al. (2004) — for Tobin's q estimation, and Brücker and Siliverstovs (2006) — for international migration, among others.

In addition to pooling, accounting for spatial interdependence between regions may prove beneficial for the purposes of forecasting. Spatial dependence implies that due to spillover effects (e.g., commuter labor and trade flows) neighboring regions may have similar economic performance and hence location matters. However, the number of studies that illustrate the usefulness of accounting for (possible) spatial dependence effects across cross-sections in the forecasting exercise is still limited. For example, Elhorst (2005), Baltagi and Li (2006), and Longhi and Nijkamp (2007) demonstrate the forecast superiority of models accounting for spatial dependence across regions using data on demand for cigarettes from states of the USA, demand for liquor in the American states, and German regional labor markets, respectively. However, only Longhi and Nijkamp (2007) conduct quasi real-time forecasts for period $t + h$ ($h > 0$) based on the information available in period t. On the other hand, the forecasts made in Elhorst (2005) and Baltagi and Li (2006) are not real-time forecasts, since they take advantage of the whole information set that is available in the forecast period, $t + h$.

Applications of panel data models accounting for spatial effects for the forecasting of regional GDP are even more limited. To our knowledge, there are only two papers treating this issue, namely that of Polasek et al. (2007), who make long-term forecasts of the GDP of 99 Austrian regions, but do not evaluate their accuracy in a formal way, and Kholodilin et al. (2008), who forecast the GDP of German Länder at horizons varying from

1 to 5 years and evaluate them in terms of the root mean square error (RMSFE).

Structural type predictions of future trend output growth for China are made by Holz (2008) and Perkins and Rawski (2008). Existing work on forecasting Chinese GDP growth relies on two series of approaches. A very aggregate on low-frequency (annual) data uses standard or modified ARIMA models (Guo, 2006) as well as genetic programming methods (Li et al. (2007)). The other branch computes composite leading indicators on disaggregated high-frequency (quarterly) data, with factor models. The latter is done either in a simple form (in the footsteps of Stock and Watson (1989)) as in Klein and Mak (2005) or Curran and Funke (2006), or with a sophisticated two-step VAR framework (à la Stock and Watson (2005) as in Qin et al. (2008). Finally, a third branch relies on macroeconometric structural models (Qin et al. (2008)). The second, or two-step factor VAR, framework seems to outperform the macro-structural one in forecasting Chinese GDP growth at a quarterly frequency (Qin et al. (2008)). None of these exploits the regional dimension of the Chinese economy to forecast GDP growth.

Thus, the main contribution of this paper is the construction of GRP forecasts for all Chinese provinces simultaneously. To the best of our knowledge, this is the first attempt to make the GRP forecast for China using spatial methods. Our additional contribution to the literature is that in order to make forecasts of GRP of provinces we employ panel data models that allow not only for temporal interdependence in the regional growth rates, but also take into account their spatial interdependence. Moreover, the possible differences in spatial effects between groups of more or less homogeneous regions are allowed. Two such groups are identified: Coast and Interior. In comparison to the Interior provinces, the Coastal provinces are much more dynamic and open. The advantage of our approach is that it is suited to conduct forecasts in the real time. We also demonstrate the usefulness of our approach by formal methods. It is shown that ooling, accounting for spatial effects, and differential treatment of Coastal and Interior provinces leads to a substantially higher forecast accuracy of the real growth rates of GRP of Chinese provinces.

The paper is structured in the following way. Section 2 reviews the studies on spatial effects among Chinese provinces. In section 3 the data are described. Section 4 presents different econometric forecasting models. In section 5 the estimation results are reported, whereas section 6 evaluates the forecasting performance of alternative models. Finally, section 7 concludes.

2 Spatial dimensions of growth in China

In this section, we review the existing literature on spatial effects among Chinese provinces. In particular, we are interested in the spatial dependences between the provinces as well as spatial heterogeneity among them.

Spatial interactions among provinces should be a positive function of the degree of integration between them. The fragmentation of China's internal market in the early 1990s was established as a stylized fact from the pioneering World Bank (1994) study to the influential work by Young (2000). Reliable evidence on the potential impact of widely reported increases in inter-provincial trade barriers in the 1990s, relies on provincial input-output tables. Early analyses of such data (Zhou, 1996; Naughton (2003)) leave out the crucial growth period following Deng's tour to the South. Work using the update of the data to 1997 uses either a trade approach or a macroeconomic approach. Relying on the former, Poncet (2003) documents a fall in inter-provincial trade after 1992. Such a conclusion even holds at the disaggregated level, as shown by Poncet (2005) who examined industry-level data. The trade diminishing impact of provincial borders (measured with McCallum (1995)'s method) indeed increased in China from 1992 to 1997.

Macroeconomic approaches have quantified the contribution of inter-regional spillover effects to regional growth in China. Based on the input-output tables for 1987 and 1997, and a 7-region aggregation of Chinese provinces, Meng and Qu (2007) identify the regions of origin of spillovers (dispersion) and those receiving them (sensitivity). Among the three most dynamic regions located on the coast, a striking contrast exists between the central Huadong (Shanghai, Jiangsu, and Zhejiang) and Southern Huanan (Fujian, Guangdong, and Hainan) on the one side and the Northern Huebei (Beijing, Tianjin, Hebei, and Shandong) on the other. The former two are national leaders in the degree of dispersion, which means their growth benefits other (especially neighboring) regions' growth, as well as each other's. By contrast the latter shows a record degree of sensitivity, benefiting primarily from growth in the two other coastal regions, but generally does not contribute to growth in other regions. Among the central inner regions, and due to its geographical location, Huazang (Shanxi, Anhui, Jianxi, Henan, Hubei, and Hunan) both shows a high sensitivity, benefiting from spillovers originating in Huadong and Huanan, and redistributes spillovers, in decreasing order to the inner regions of Xibei (Inner Mongolia, Shaanxi, Gansu, Qinghai, Ningxia, and Xingjiang), Huabei and Huanan. Xibei is one of the typical beneficiaries of spillovers, but also originates them due to its "exports" of natural resources. Due to their low dispersion and sensitivity degrees, the Northeastern region of Dongbei (Liaoning, Jilin, and Heilongjinag) and the Southwestern Xianan (Guangxi, Choongqin, Sichuan, Guizhou, Yunnan, and Tibet) look similar as a result of their remote geographical locations. However, the latter has taken advantage of its proximity and good access to the high-dispersion generating Hanan.

Luo (2005) encompasses the above approaches. He takes on board the importance of the border effect, focuses the microscope with a finer resolution, and gives it a time-series dimension. He uses panel data on real per capita GDP growth to examine spillover effects between neighboring provinces which share a common border. Leaving out the municipalities (Beijing, Shanghai, and Tianjin), the provinces in the three coastal regions of Huabei, Huadong, and Huanan have generated the largest spillovers (dispersion) effects over the 1978-1999 period. However due to the focus on border effects only, the induced growth (sensitivity) has mainly been concentrated in the coastal region itself, with limited effects on Central, let alone Western, regions. One notable exception is Guangdong, which is the top disperser to the benefit of provinces located in both central and Western regions. Among Inland provinces, both Hubei and Sichuan have generated substantial dispersion effects not limited to their own regions.

Spatial statistical methods are used by Aroca et al. (2006) to show that spatial dependence of provincial per capital GDP in China increased very substantially over the five decades of its economic development. Spatial dependence, as measured by Moran's I shows a rise in spatial interactions particularly notable in the 1990s. Comparing 1952, 1978, and 1999, a positive relationship between provincial GDP per capita and its spatial lag (Moran's scatterplot) only arises in the latter period. This has been due in great part the change of status of Beijing and Shanghai from a slightly negative to a very strongly positive relationship. Sandberg (2004) finds that the Moran's I test is positive only for the second half of the 1990s. In other words, provinces with similar growth rates are more clustered than chance would imply. In addition, over the whole 1985-2000 period, provinces other than direct neighbors are relatively isolated from each other. Ying (2003) finds that according to Moran's I test, the strongest pattern of spatial autocorrelation is manifest for a distance of 2000 kilometers. In line with Anselin and Rey (1991)'s criticism of Moran's test, he further distinguishes between spatially autocorrelated errors (often due to a mismatch between economic and administrative boundaries) and spatial lag dependence (due to spillovers across provinces). The Lagrange multiplier test for the 2000 km distance (as well as for others) implies that the spatial lag is significant, while spatial autocorrelation is not. In his Solow-type growth regression estimates, the spatial lag variable indeed takes into account spatial autocorrelation, and adequately represents the spatial effects in the Chinese economy.

To summarize, the above mentioned studies do recognize the importance of the spatial dependences between Chinese provinces. In addition, the literature acknowledges the spatial heterogeneity existing between the interior and coastal provinces.

3 Data description

For estimation and forecasting we use the growth rates of the annual real Gross Regional Product (GRP) for the 31 Chinese regions (including 22 provinces, 4 municipalities, and 5 autonomous regions). Following the widely accepted, although a bit misleading, practice we will denote Chinese regions as provinces, regardless of whether they are provinces, municipalities or autonomous regions. The data cover the period 1979-2007 and were obtained from the National Bureau of Statistics of China. The data are the chain indices of GRP with the base year 2000.

The basic descriptive statistics of the growth rates of real GDP in form of the mean, maximum, minimum, and the standard deviation are reported in Table 1. In addition, these descriptive statistics were computed for the two groups of Chinese provinces (Coast and Interior) as displayed in the map of China — see Figure 1. The provinces belonging to the Coast group grow faster and in a more stable way than those belonging to the Interior group. Using the GRP data covering the whole period and the trade and foreign direct investment (FDI) data borrowed from Sheng (2009) and covering the period of high growth, 1992-2006, it can be shown that Coast provinces have a far higher openness degree (both in terms of trade-to-GRP and exports-to-GRP ratios) and attract much more FDI compared to their GRP than the Interior provinces — see Table 2. For example, alhough the growth rates in both groups of provinces differ by only 1.5 percentage points, the trade-to-GRP ratio in Coastal provinces is 2.5 times higher than in the Interior provinces and the FDI-to-GRP ratio is 1.2 times higher. Thus, it can be expected that such a different economic structure can translate into different spatial dependence.

4 Alternative models

In this section, we describe the econometric models that we are used for forecasting the growth rates of real GDP of Chinese provinces.

We examine a standard set of dynamic panel data (DPD) models starting with individual autoregressive (AR) models, which can be considered as a particular case of DPD models with unrestricted parameters, through fixed-effects models, which impose homogeneity restrictions on the slope parameters, to pooled models, which impose homogeneity restrictions on both intercept and slope parameters. In addition to standard fixed-effects and pooled models, we also consider fixed-effects and pooled models that account for spatial dependence.

As a benchmark model, with which all other models will be compared, we use a linear *individual AR(1)* model (I_{OLS}) and estimate it for each province separately:

$$y_{it} = \alpha_i + \beta_i y_{it-1} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma_i^2) \tag{1}$$

where y_{it} is the annual growth rate of real GDP of i-th province.

In addition, given the short time dimension of our data, it should be noted that the OLS estimator of the parameters of individual AR(1) models is biased due to insufficient degrees of freedom as pointed out in Ramanathan (1995).

The next model we consider is the *pooled panel*, P_{OLS}, model:

$$y_{it} = \alpha + \beta y_{it-1} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{2}$$

which imposes the homogeneity restriction on both intercept and slope coefficients across all the provinces.

An alternative model is the *fixed-effects*, F_{OLS}, model that allows for province-specific intercepts:

$$y_{it} = \alpha_i + \beta y_{it-1} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{3}$$

The fixed-effects model represents an intermediate case between the individual, I_{OLS}, and pooled panel, P_{OLS}, models. It is not too restrictive as the pooled model, which assumes equal average growth rates in all provinces, and yet allows to take advantage of panel dimension. From the economic point of view, fixed effects capture differences in growth rates between provinces related to their heterogeneous economic structure.

Moreover, considering a *group-effects*, G_{OLS}, where the intercepts are group-specific, might be useful:

$$y_{it} = \sum_{g=1}^{G} I_g \alpha_g + \beta y_{it-1} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{4}$$

where G is the number of groups of provinces ($1 < G < N$, where N is the number of provinces) and I_g is the group dummy, which is equal to one, when the province belongs to group g, and to zero, otherwise. As shown in section 3, two major groups of provinces in China can be identified: Coast and Interior. These groups of provinces differ both in terms of level of economic development and in terms of the growth rate. Therefore, it would be reasonable to assume that the intercepts of for each group can be different. Hence, $G = 2$ and group dummies represent a group of coastal and a group of interior provinces. The group-effects model can be considered as an intermediate case between the pooled model and the fixed-effects model.

Additionally, we consider the following two types of models that account for spatial correlation that might exist between the provinces. One may expect to find the dynamic (stagnating) provinces being the neighbors of dynamic (stagnating) provinces due to cross-border spillovers (commuter labor and trade flows).

The spatial dependence is accounted for using an $N \times N$ matrix of spatial weights W, which is based on the distance between the centroids of respective provinces[1]. Following Baumont et al. (2002) we constructed four distance-decay weights matrices depending on four different distance cutoff values: first quartile, median, second quartile, and maximum distance. The forecast accuracy of the models based on these weights matrices was more or less similar. Therefore, in order to save space we will report here only results obtained for the median as a distance cutoff value. The typical element of this matrix, w_{ij}, is defined as:

$$w_{ij} = \frac{1}{d_{ij}^2} \tag{5}$$

where d_{ij} is the great circle distance between the centroids of province i and province j.

Moreover, all the elements on the main diagonal of matrix W are equal to zero. The constructed weights

[1]The use of a matrix of spatial weights based on existence of common borders between the provinces is complicated by the fact that there are island provinces, such as Hainan.

matrix is normalized such that all the elements in each row sum up to one.

First, we model the spatial dependence by means of spatial lags of the dependent variable. We examine both pooled and fixed-effects versions of this model. The *pooled spatial lag* model (P^{SLM}_{MLE}) can be written as follows:

$$y_{it} = \alpha + \beta y_{it-1} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{6}$$

The *group-effects spatial lag* model (G^{SLM}_{MLE}) is:

$$y_{it} = \sum_{g=1}^{G} I_g \alpha_g + \beta y_{it-1} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{7}$$

The *fixed-effects spatial lag* model (F^{SLM}_{MLE}) is:

$$y_{it} = \alpha_i + \beta y_{it-1} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{8}$$

where ρ is the spatial autoregressive parameter and N is the number of provinces.

The second type of models addresses spatial correlation through a spatial autoregressive error structure, as suggested by Elhorst (2005). Again, we distinguish between pooled and fixed-effects models. Due to their specific nature, those models are estimated by the Maximum Likelihood method (MLE). The *pooled spatial error* model (P^{SEM}_{MLE}) has the following form:

$$y_{it} = \alpha + \beta y_{it-1} + u_{it} \quad u_{it} = \lambda \textstyle\sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{9}$$

The *group-effects spatial error* model (G^{SEM}_{MLE}) can be defined as:

$$y_{it} = \sum_{g=1}^{G} I_g \alpha_g + \beta y_{it-1} + u_{it} \quad u_{it} = \lambda \textstyle\sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{10}$$

The *fixed-effects spatial error* model (F_{MLE}^{SEM}) can be expressed as:

$$y_{it} = \alpha_i + \beta y_{it-1} + u_{it} \quad u_{it} = \lambda \textstyle\sum_{j=1}^{N} w_{ij} u_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{11}$$

where λ is the coefficient of spatial error autoregression.

However, it may be argued that the spatial dependence, as measured by the spatial correlations, should not necessarily be the same for all the provinces. It may well be the case that spatial correlations within groups encompassing more or less homogeneous provinces can be different. Based on this hypothesis Garrett et al. (2007) suggest a model with group-specific spatial dependence. As usual, both pooled and fixed-effects models can be defined, which are estimated using MLE.

The *pooled spatial lag model with group-specific spatial dependence* (P_{MLE}^{SLM-G}) can be formulated as:

$$y_{it} = \alpha + \beta y_{it-1} + \sum_{g=1}^{G} \sum_{j=1}^{N} \rho_g w_{ij}^g y_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{12}$$

where w_{ij}^g is a typical element of the group-specific spatial weights matrix, W^G, which is constructed by pre-multiplying by a dummy variable that equals unity if province i is located in group g, and zero otherwise, see Garrett et al. (2007), p. 607.

The *group-effects spatial lag model with group-specific spatial dependence* (G_{MLE}^{SLM-G}) can be expressed as:

$$y_{it} = \sum_{g=1}^{G} I_g \alpha_g + \beta y_{it-1} + \sum_{g=1}^{G} \sum_{j=1}^{N} \rho_g w_{ij}^g y_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{13}$$

This model accounts both for heterogeneity in average growth rates and spatial dependence between the groups of provinces.

The *fixed-effects spatial lag model with group-specific spatial dependence* (F_{MLE}^{SLM-G}) can be expressed as:

$$y_{it} = \alpha_i + \beta y_{it-1} + \sum_{g=1}^{G} \sum_{j=1}^{N} \rho_g w_{ij}^g y_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{14}$$

The *pooled spatial error model with group-specific spatial dependence* (P_{MLE}^{SEM-G}) has the following form:

$$y_{it} = \alpha + \beta y_{it-1} + u_{it} \quad u_{it} = \sum_{g=1}^{G} \sum_{j=1}^{N} \lambda_g w_{ij}^g u_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{15}$$

The *group-effects spatial error model with group-specific spatial dependence* (G_{MLE}^{SEM-G}):

$$y_{it} = \sum_{g=1}^{G} I_g \alpha_g + \beta y_{it-1} + u_{it} \quad u_{it} = \sum_{g=1}^{G} \sum_{j=1}^{N} \lambda_g w_{ij}^g u_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{16}$$

Finally, the *fixed-effects spatial error model with group-specific spatial dependence* (G_{MLE}^{SEM-G}):

$$y_{it} = \alpha_i + \beta y_{it-1} + u_{it} \quad u_{it} = \sum_{g=1}^{G} \sum_{j=1}^{N} \lambda_g w_{ij}^g u_{jt} + \varepsilon_{it} \quad \varepsilon_{it} \sim N.I.D.(0, \sigma^2) \tag{17}$$

We have estimated I_{OLS}, P_{OLS}, G_{OLS}, and F_{OLS} using the OLS method. It is known from the literature that in the context of dynamic panel data models the OLS estimator is subject to simultaneous equation bias. In order to address this problem we have used the GMM estimator of Arellano and Bond (1991) to estimate the fixed-effects model without spatial autoregressive lags. Notice that the GMM estimator uses the first-difference transformation, which omits the time-invariant variables (in our case, the province-specific intercepts). These were recovered using the following two-step procedure. In the first step, the slope parameters are estimated using the first differences of the data. In the second step, the estimated parameters are plugged into the equation for the levels of data and the fitted values are calculated. The fixed effects for the F_{GMM} model are obtained as the province-specific averages of a difference between actual and fitted values.

Although from the theoretical perspective, the GMM estimators should be preferred to the OLS estimators when applied to dynamic panels with small time dimension, in what follows we use the OLS estimators[2], since in the forecasting context a biased but stable estimator may still deliver a more accurate forecasting performance than an unbiased but unstable one.

The remaining dynamic panel models accounting for spatial effects were estimated using the Maximum Likelihood method as implemented in the Ox codes written by Konstantin A. Kholodilin[3].

[2]The computations were performed using the DPD package for Ox, see Doornik et al. (2006).

[3]The codes are available upon request. For details about the Ox programming language see Doornik and Ooms (2006).

5 Estimation results

The estimates of the temporal and spatial autoregressive coefficients of all the models are presented in Table 3.

First, we report a summary of the estimates of intercept, $\widehat{\alpha}$, and the temporal autoregressive coefficient, $\widehat{\beta}$, obtained for an autoregressive model estimated for each province separately and reported in columns (1) and (2) of Table 3. To save space only lowest and highest parameter estimates are reported. The smallest intercept is estimated at 3.278 for Hunan, while the largest one at 10.949 for Henan. The first coefficient estimate is not statistically significant, whereas the second one is statistically significant. The smallest temporal autoregressive coefficient (-0.156) is estimated for Qinghai province, whereas the largest (0.669) for Hunan province. Both these coefficients are statistically significant. The intercept and autoregressive coefficient estimated for 1979-2007 imply that the conditional mean of the growth rate in Chinese provinces should vary between 8.8% and 14.1%. In addition, the individual autoregressive models seem to provide quite a good fit to the data, since the values of the R^2 are relatively high: in two thirds of the cases they exceed 0.8.

The columns (3) through (5) of Table 3 contain the estimation results obtained for the pooled model (equation 2), group-effects (equation 4), and for the fixed-effects model (equation 3) using OLS. All the intercept estimates are positive and significant. Under the group-effects model, G_{OLS}, the intercept estimate for Coastal provinces, $\widehat{\alpha}_1$, is higher than that for the Interior provinces, $\widehat{\alpha}_2$. This reflects the fact that the Coast provinces have been growing in 1979-2007 on average faster than the provinces of Interior, as also Table 1 shows. The estimates of temporal autoregressive parameters for these models are significant and positive and very close to the median autoregressive parameter estimate of the individual models. The goodness-of-fit of the panel models without spatial effects is larger than that of the individual models, whose median R^2 is equal to 0.149.

The columns (6) through (10) of Table 3 report the parameter estimates of the panel models accounting for spatial dependence but assuming that it is identical. As in case of group-effects model, which does not account for spatial dependence, the intercept estimates for Coastal provinces are higher than those for the Interior provinces both for G_{MLE}^{SLM} and G_{MLE}^{SEM} model. Again, the estimates of the temporal autoregressive coefficients are positive and significant, but substantially smaller than those of the models without spatial effects. The estimated spatial autoregressive coefficients are highly significant and positive. This points out to the importance of spatial dependence among Chinese provinces. The R^2's are more than twice as large as those of the panel models without spatial effects.

Finally, the columns (11) through (17) of Table 3 contain the parameter estimates of the models that allow for group-specific spatial effects. The estimates of the temporal autoregressive coefficients are significant and similar to those of the panel models with identical spatial dependence. In each model, three spatial autoregressive coefficients are estimated, for, as described in Table 1, all 31 Chinese provinces were classified into two groups: Coast and Interior. All these estimates are positive and statistically significant. The spatial autoregressive coefficient for the Coast is bigger than that of Interior in case of the spatial lag model and smaller in case of the spatial error model. The goodness-of-fit measures for these last four models are similar to those of the panel models with identical spatial dependence.

To summarize, on the basis of our estimation results we conclude the following. First, in most cases, the temporal autoregression is statistically significant and thus past GRP values appear to play an important role in explaining its future values. Second, the spatial dependence is also statistically significant, which implies that there is a relatively high degree of dependence of economic performance among neighboring provinces. Third, this spatial dependence seems to be different within the Coastal group and Interior group of provinces. Fourth, the panel-data models with spatial dependence appear to fit the data better than the panel-data models without spatial dependence and the individual models.

6 Forecasting performance

For each model we forecast recursively the h-year growth rates of real GDP, $\Delta^h y_{i,t+h} = y_{i,t+h} - y_{it}$ for $h = 1, 2, \ldots, 15$ for all 31 provinces over the forecasting period encompassing the period 1989-2007. This procedure gives us $(15 - (h-1)) \times N$ forecasts for the h-year growth rate.

For each model, the parameter estimates were obtained using either an expanding window or rolling window of observations. Under expanding window, the first estimation period is 1979-1988, based on which the forecasts of $\Delta^1 y_{i,1989}, \Delta^2 y_{i,1990}, \ldots, \Delta^{15} y_{i,2003}$ are made. Next, the model is re-estimated for the period 1979-1989 and the forecasts $\Delta^1 y_{i,1990}, \Delta^2 y_{i,1991}, \ldots, \Delta^{15} y_{i,2004}$ are computed, etc. Alternatively, under rolling window, the first estimation period is 1979-1988, based on which the forecasts of $\Delta^1 y_{i,1989}, \Delta^2 y_{i,1990}, \ldots, \Delta^{15} y_{i,2003}$ are made. Next, the model is re-estimated for the period 1980-1989 and the forecasts $\Delta^1 y_{i,1990}, \Delta^2 y_{i,1991}, \ldots, \Delta^{15} y_{i,2004}$

are computed, etc.

For all models, except spatial lag models, the forecasts were made in a standard way. The forecasts of the spatial lag models are conducted using a two-step procedure. In order to illustrate this procedure, it is worthwhile re-writing the spatial lag models (6) and (8) in the following matrix form for the pooled:

$$\mathbf{y} = \alpha \boldsymbol{\imath}_{NT} + \beta \mathbf{y}_{-1} + \rho \mathbf{W}\mathbf{y} + \boldsymbol{\varepsilon} \tag{18}$$

for the fixed-effects:

$$\mathbf{y} = (\boldsymbol{\imath}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + \beta \mathbf{y_{-1}} + \rho \mathbf{W}\mathbf{y} + \boldsymbol{\varepsilon} \tag{19}$$

where $\mathbf{y}$ is a $NT \times 1$ vector of the y_{it} stacked by year and province such that the first N observations refer to the first year, etc. Correspondingly, $\mathbf{y_{-1}}$ is a $NT \times 1$ vector of the $y_{i,t-1}$ stacked by year and province. $\mathbf{I}_N$, $\mathbf{I}_T$, and $\mathbf{I}_{NT}$ are the unit matrices with dimensions $N \times N$, $T \times T$, and $NT \times NT$, respectively. The $NT \times NT$ matrix $\mathbf{W} = \mathbf{I}_T \otimes W$ is the block-diagonal matrix with the $N \times N$ matrix W of spatial weights on its main diagonal, where is $\otimes$ a Kronecker product. $\boldsymbol{\imath}_{NT}$ and $\boldsymbol{\imath}_T$ are the NT and T unit vectors, respectively, such that α and $\boldsymbol{\alpha}$ are correspondingly a common intercept and an $N \times 1$ vector of cross-section specific intercepts in the pooled and the fixed-effects spatial lag models.

The models (18) and (19) can be re-written in the following reduced form:

$$\begin{aligned} (\mathbf{I_{NT}} - \rho \mathbf{W})\mathbf{y} &= \alpha \boldsymbol{\imath}_{NT} + \beta \mathbf{y}_{-1} + \boldsymbol{\varepsilon} \\ \mathbf{y} &= (\mathbf{I_{NT}} - \rho \mathbf{W})^{-1}[\alpha \boldsymbol{\imath}_{NT} + \beta \mathbf{y}_{-1}] + (\mathbf{I_{NT}} - \rho \mathbf{W})^{-1}\boldsymbol{\varepsilon} \end{aligned} \tag{20}$$

$$\begin{aligned} (\mathbf{I_{NT}} - \rho \mathbf{W})\mathbf{y} &= (\boldsymbol{\imath}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + \beta \mathbf{y_{-1}} + \boldsymbol{\varepsilon} \\ \mathbf{y} &= (\mathbf{I_{NT}} - \rho \mathbf{W})^{-1}[(\boldsymbol{\imath}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + \beta \mathbf{y_{-1}}] + (\mathbf{I_{NT}} - \rho \mathbf{W})^{-1}\boldsymbol{\varepsilon} \end{aligned} \tag{21}$$

where only the past values of $\mathbf{y}$ appear on the right-hand side of the equations.

In the case of the models with group-specific spatial dependence, these forecasting equations can be easily generalized as follows. For the pooled model with group-specific spatial dependence, the forecasting equation will look like:

$$
\begin{aligned}
(\mathbf{I_{NT}} - \tilde{\mathbf{W}})\mathbf{y} &= \alpha \boldsymbol{\imath}_{NT} + \beta \mathbf{y}_{-1} + \boldsymbol{\varepsilon} \\
\mathbf{y} &= (\mathbf{I_{NT}} - \tilde{\mathbf{W}})^{-1} [\alpha \boldsymbol{\imath}_{NT} + \beta \mathbf{y}_{-1}] + (\mathbf{I_{NT}} - \tilde{\mathbf{W}})^{-1} \boldsymbol{\varepsilon} \qquad (22)
\end{aligned}
$$

where $\tilde{\mathbf{W}} = \mathbf{I}_T \otimes \left[\sum_{g=1}^{G} \rho_g W^g \right]$.

The forecasting equation for the fixed-effects model with group-specific spatial dependence can be expressed as:

$$
\begin{aligned}
(\mathbf{I_{NT}} - \tilde{\mathbf{W}})\mathbf{y} &= (\boldsymbol{\imath}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + \beta \mathbf{y_{-1}} + \boldsymbol{\varepsilon} \\
\mathbf{y} &= (\mathbf{I_{NT}} - \tilde{\mathbf{W}})^{-1} [(\boldsymbol{\imath}_T \otimes \mathbf{I}_N)\boldsymbol{\alpha} + \beta \mathbf{y_{-1}}] + (\mathbf{I_{NT}} - \tilde{\mathbf{W}})^{-1} \boldsymbol{\varepsilon} \qquad (23)
\end{aligned}
$$

The multi-step ahead forecasts from the spatial lag models can now be obtained as follows. First, we estimate the parameters of the models (18) and (19), as outlined above. Second, we use the reduced form equations (20) and (21) for the models with identical spatial dependence or equations (22) and (23) for the models with group-specific spatial dependence in order to generate the forecasts.

The estimation of all forecasting models was conducted using both expanding window and rolling 9-year window. The advantage of the growing-window estimation is that each period the estimation sample is increased by one observation and hence the small-sample uncertainty of parameter estimates should diminish. However, looking at the GRP dynamics of Chinese provinces in 1979-2007 (see Figure 2) one can observe at least three distinct periods: 1979-1989, 1990-1998, and 1999-2007. These periods are characterized by different dynamics and hence probably by different parameter values. Therefore, using a rolling window might be useful, as its parameter estimates depend on the recent past only and hence react quicker to the possible structural breaks. The disadvantage of rolling-window estimation, especially for non-panel models, is that the number of observations might be too small to guarantee an accurate enough estimation of parameters.

The results of our forecasting exercise are reported in Table 4 for expanding window and Table 5 for rolling window. The forecasting performance is measured by the root mean square forecast error (RMSFE) calculated for all years and over all provinces for each forecasting horizon, $h = 1, 2, \ldots, 15$.

First, the use of growing versus rolling window is compared. In case of the following six models rolling window leads to a better forecast accuracy at all or most forecast horizons: P_{OLS}, G_{OLS}, F_{OLS}, P^{SEM}_{MLE}, P^{SEM2}_{MLE}, and G^{SEM2}_{MLE}. For the remaining models, under the rolling window, either at all or at more than a half of horizons the forecast accuracy deteriorates. While the improvement varies between 1% and 8% compared to the growing-window estimation, the deterioration attains even 85%. The models with fixed-effects, which have even poorer forecast accuracy, are excluded from consideration as inadequate in this context (see below). Hence, it is not at all evident that the rolling-window estimation brings better forecast accuracy. However, it still can be useful, since it improves the forecasting performance of the already more accurate models.

Second, the panel models are compared to the naive models. Naive model 1, which uses previous period value as a forecast, is almost always worse than all other models, regardless of estimation window. Only at horizon $h = 1$ it produces more accurate forecasts than other non-panel models and even some panel models (generally, fixed-effects models). The naive model 2, which uses an average of past growth rates as a forecast, is worse than all panel models at all forecast horizons and worse than I_{OLS} model at horizons from $h = 1$ through $h = 4$, when estimated using expanding window. Under the rolling-window estimation, the naive model 2 is less accurate at all horizons than P_{OLS}, G_{OLS}, F_{OLS}, P^{SEM}_{MLE}, G^{SEM}_{MLE}, P^{SEM2}_{MLE}, and G^{SEM2}_{MLE} models and less accurate at most horizons than P^{SLM}_{MLE} and G^{SLM}_{MLE} models. Thus, the naive models are inferior in terms of the forecast accuracy than the pooled and group-effects panel models.

Third, the individual autoregressive models, I_{OLS}, are compared to the panel models. The results of our forecasting exercise further strengthen the evidence previously reported in a number of studies such as Baltagi and Griffin (1997); Baltagi et al. (2003), Baltagi et al. (2000), Baltagi et al. (2002), Baltagi et al. (2004), and Brücker and Siliverstovs (2006), Kholodilin et al. (2008) among others, that pooling helps to improve forecast accuracy. Under the expanding window, the individual AR model is less accurate than all the panel models at all forecast horizons. The two exceptions are F^{SEM}_{MLE} and F^{SEM2}_{MLE} that are worse than I_{OLS} at the early horizons: from $h = 1$ till $h = 3$. Under the rolling window, the individual AR model has lower forecasting performance than all the panel models, but F^{SEM}_{MLE} and F^{SEM2}_{MLE} as well as F^{SLM2}_{MLE}, which is substantially worse than the individual AR model at horizons from $h = 1$ through $h = 13$.

Fourth, the panel models can be ranked in terms of their forecast accuracy as follows. As a rule, the group-effects models are better than the pooled ones, which, in turn, are much better than the fixed-effects models. There are the following few exceptions: 1) under growing-window estimation, G_{MLE}^{SLM2} is worse than P_{MLE}^{SLM2}; 2) under rolling-window estimation, G_{MLE}^{SLM} and G_{MLE}^{SLM2} are worse than the corresponding pooled models.

Fifth, as expected, the application of panel models accounting for spatial effects as a rule results in a better forecast accuracy compared to the corresponding non-spatial models. Regardless of whether the models were estimated using growing or rolling window, the pooled and group-effects models accounting for spatial effects always produce more accurate forecasts than their non-spatial counterparts. This is not always true for the fixed-effects models, but, as shown above, they appear to be inadequate as forecasting models in the present context and hence can be discarded.

Sixth, homogeneous spatial effects vs. heterogeneous spatial effects. Under the expanding window, P_{MLE}^{SLM2} and P_{MLE}^{SEM2} are better than their counterparts,P_{MLE}^{SLM} and P_{MLE}^{SEM}, not accounting for the possible heterogeneity of spatial dependence within Coast and Interior groups of provinces. Increase in forecast accuracy due to accounting for heterogeneity of spatial dependence varies between 1% and 13%. In case of group-effects models, there is no improvement or there is even a slight deterioration of the forecasting performance. Under the rolling-window estimation, the forecast accuracy of all the spatial-error models improves when group-specific spatial dependence is accounted for. The forecast accuracy gain, however, is quite small, varying between 1% and 5%. In case of spatial-lag models, the forecast accuracy substantially deteriorates but under the rolling window in the Chinese regional context they seem to be inadequate as forecasting models.

Seventh, the following best forecasting models can be identified. Under the expanding window, the two best models are: G_{MLE}^{SLM} at horizons from $h = 1$ through $h = 4$ and from $h = 12$ through $h = 14$ and G_{MLE}^{SEM2} at horizons $h = 5$ and horizons from $h = 8$ through $h = 11$. In addition, G_{MLE}^{SEM} is the best at horizon $h = 6$ and $h = 7$, whereas G_{MLE}^{SLM2} is the best at horizon $h = 15$. When the individual autoregressive model estimated under the expanding window, I_{OLS}, is used as a benchmark, then the forecast accuracy gain, measured as a ratio of the RMSFE of the corresponding best model to that of I_{OLS}, varies between 6% at horizon $h = 2$ and 27% at horizon $h = 13$. Under the rolling window, the clear leader of forecasting accuracy is the model G_{MLE}^{SEM2}, which is the most accurate at forecast horizons from $h = 2$ through $h = 14$. The other best two models are P_{MLE}^{SLM} that is the best at horizon $h = 1$ and G_{MLE}^{SLM} that is the best at horizon $h = 15$. The forecast accuracy gain (again measured with respect to the individual autoregressive model estimated under the expanding window, because the use of rolling window leads systematically worse performance of I_{OLS}) varies between 7% at horizons $h = 2$ and $h = 3$ and 27% at horizon $h = 15$. As a general rule, regardless of estimation window, the forecast accuracy gets larger at higher forecast horizons.

To summarize, pooling, accounting for spatial effects, and using group dummies instead of a single intercept contribute the most to the improvement in forecast accuracy. Additional, albeit smaller, improvements stem from accounting for the fact that spatial effects may be different depending on the group of provinces. In this case, taking into account the differences between Coast and Interior both in terms of intercept and in terms of spatial dependence clearly leads to a better forecast accuracy.

The robustness of these results can be checked by observing Figures 3-5, which show the RMSFE computed for 1-, 5-, and 10-year ahead forecasts with a rolling 3-year window. The boxplots represent the distribution of the RMSFE of all the model examined in this paper. In addition, the AR(1) model estimated using an expanding window, I_{OLS}, and the best model accounting for spatial effects estimated using a rolling window, G_{MLE}^{SEM2}, are shown. Recall that AR(1) estimated using a rolling window has a very poor forecasting performance.

Several observations can be made using these graphs. Firstly, the forecast accuracy of all the models has not been constant: It increased from 1989 till the mid-1990s, then it dropped substantially (5 times for the 1-year ahead forecasts, 2 times for the 5-year ahead forecasts, and about 1.5 times for the 10-year ahead forecasts) and attained its minimum around 2001, after which it slightly increased again. Such a profile can be explained by the interplay of many factors. One reason can be a purely econometric one — increasing the sample size leads to an improvement in parameter estimates and hence forecast accuracy. Another reason can be the influence of economic downturns — during turmoil periods the economy is generally considered to be more difficult to forecast.

Secondly, the rolling RMSFE for the 1-year ahead forecasts of G_{MLE}^{SEM2} is systematically lower than that of the AR(1) model. Most of the time it is also lower than the median rolling RMSFE. In addition, in the beginning of the sample 1989-1995, the RMSFE of G_{MLE}^{SLM-2} is close to the minimum. The AR(1) model is usually close to the median, although in the very beginning and end of sample its RMSFE exceeds the median RMSFE.

Thirdly, it is at the higher forecast horizons (5- and especially 10-year ahead forecasts) that the G_{MLE}^{SLM-2}

model significantly improves upon the I_{OLS} model and all other models. Thus, at 5-year horizon its rolling RMSFE is close to the 1st quartile and minimum of the distribution starting from subperiod 1994-1996. However, during 1991-1995 period it is worse than the AR(1) model. At the 10-year ahead forecast horizon, the G^{SLM-2}_{MLE} model is always better than I_{OLS} model and the gap between both models increases towards the end of sample. Moreover, the RMSFE of the G^{SLM-2}_{MLE} model is systematically lower than the median rolling RMSFE.

Thus, during the most of the sample period at higher forecast horizons our best model, G^{SEM2}_{MLE}, seems to be more accurate than the alternative models.

7 Conclusion

In this paper, we have addressed the forecasting of h-year growth rates of real GDP for of each of the 31 Chinese provinces using dynamic panel data models with spatial effects, $h = 1, 2, \ldots, 15$.

Our main finding is that pooled models accounting for spatial dependence, in particular the models allowing for group-specific spatial effects, produce the best forecasting accuracy (as measured by the Root Mean Squared Forecast Error) compared to any other model examined in this paper. This finding remains robust across all forecasting horizons but especially high forecast accuracy gains are obtained at high forecast horizons.

Two factors must have contributed to this improvement: pooling and accounting for spatial effects. On the one hand, the finding that pooling helps to increase the forecasting accuracy is consistent with the results obtained in Baltagi and Griffin (1997); Baltagi et al. (2003), Baltagi et al. (2000), Baltagi et al. (2002), Baltagi et al. (2004), and Brücker and Siliverstovs (2006), *inter alia*, for diverse data sets. On the other hand, the fact that accounting for spatial effects helps to improve the forecast performance further strengthens conclusions of Elhorst (2005), Longhi and Nijkamp (2007), and Kholodilin et al. (2008).

Hence, on the basis of our results, we strongly recommend incorporating spatial dependence structure into regional forecasting models, especially, when long-run forecasts are made.

References

Anselin, L. and S. Rey (1991). Properties of tests for spatial dependence in linear regression models. *Geographical Analysis 23*, 112–131.

Arellano, M. and S. Bond (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies 58*(2), 277–97.

Aroca, P., D. Guo, and G. J. Hewings (2006). Spatial convergence in China: 1952-99. Working Papers RP2006/89, World Institute for Development Economic Research (UNU-WIDER).

Baltagi, B. H., G. Bresson, J. M. Griffin, and A. Pirotte (2003). Homogeneous, heterogeneous or shrinkage estimators? Some empirical evidence from French regional gasoline consumption. *Empirical Economics 28*(4), 795–811.

Baltagi, B. H., G. Bresson, and A. Pirotte (2002). Comparison of forecast performance for homogeneous, heterogeneous and shrinkage estimators: Some empirical evidence from US electricity and natural gas. *Economics Letters 76*(3), 375–382.

Baltagi, B. H., G. Bresson, and A. Pirotte (2004). Tobin q: Forecast performance for hierarchical Bayes, shrinkage, heterogeneous and homogeneous panel data estimators. *Empirical Economics 29*(1), 107–113.

Baltagi, B. H. and J. M. Griffin (1997). Pooled estimators vs. their heterogeneous counterparts in the context of dynamic demand for gasoline. *Journal of Econometrics 77*(2), 303–327.

Baltagi, B. H., J. M. Griffin, and W. Xiong (2000). To pool or not to pool: Homogeneous versus hetergeneous estimations applied to cigarette demand. *The Review of Economics and Statistics 82*(1), 117–126.

Baltagi, B. H. and D. Li (2006). Prediction in the panel data model with spatial correlation. *Spatial Economic Analysis 1*, 175–185.

Baumont, C., C. Ertur, and J. Le Gallo (2002). The European regional convergence process, 1980-1995: Do spatial regimes and spatial dependence matter? mimeo.

Brücker, H. and B. Siliverstovs (2006). On the estimation and forecasting of international migration: How relevant is heterogeneity across countries? *Empirical Economics 31*(3), 735–754.

Curran, D. and M. Funke (2006). Taking the temperature — forecasting GDP growth for mainland China. BOFIT Discussion Papers 6/2006, Bank of Finland, Institute for Economies in Transition.

Doornik, J. A., M. Arellano, and S. Bond (2006). Panel data estimation using DPD for Ox. Mimeo.

Doornik, J. A. and M. Ooms (2006). *Introduction to Ox*. London: Timberlake Consultants Press.

Elhorst, J. P. (2005). Unconditional maximum likelihood estimation of linear and log-linear dynamic models for spatial panels. *Geographical Analysis 37*, 85–106.

Garrett, T., G. Wagner, and D. Wheelock (2007). Regional disparities in the spatial correlation of state income growth, 1977-2002. *The Annals of Regional Science 41*(3), 601–618.

Holz, C. A. (2008). China's economic growth 1978-2025: What we know today about China's economic growth tomorrow. *World Development 36*(10), 1665–1691.

Kholodilin, K. A., B. Siliverstovs, and S. Kooths (2008). A dynamic panel data approach to the forecasting of the GDP of German Länder. *Spatial Economic Analysis 3*(2), 195–207.

Klein, L. and W. Mak (2005). Initial steps in high-frequency modeling of China. *Business Economics 40*, 11–14.

Li, M., G. Liu, and Y. Zhao (2007). Forecasting GDP growth using genetic programming. Proceedings of the Third International Conference on Natural Computation - Volume 04, IEEE Computer Society Washington, DC.

Longhi, S. and P. Nijkamp (2007). Forecasting regional labor market developments under spatial heterogeneity and spatial correlation. *International Regional Science Review 30*, 100–119.

Luo, X. (2005). Growth spillover effects and regional development patterns: The case of Chinese provinces. Policy Research Working Paper Series 3652, The World Bank.

McCallum, J. (1995). National borders matter: Canada-U.S. regional trade patterns. *American Economic Review 85*(3), 615–23.

Meng, B. and C. Qu (2007). Application of the input-output decomposition technique to China's regional economies. IDE Discussion Papers 102, Institute of Developing Economies, Japan External Trade Organization (JETRO).

Naughton, B. (2003). How much can regional integration do to unify Chinas markets? In N. Hope, D. Yand, and M. Li (Eds.), *How Far Across the River? Chinese Policy Reform at the Millenium*, pp. 204–232. Stansdford University press.

Perkins, D. and T. Rawski (2008). Forecasting China's economic growth to 2025. In L. Brandt and T. Rawski (Eds.), *China's Great Transformation*, pp. 829–886. Cambridge.

Polasek, W., R. Sellner, and W. Schwarzbauer (2007). Long-term spatial forecasts for regional systems. mimeo.

Poncet, S. (2003). Measuring Chinese domestic and international integration. *China Economic Review 14*(1), 1–21.

Poncet, S. (2005). A fragmented China: Measure and determinants of Chinese domestic market disintegration. *Review of International Economics 13*(3), 409–430.

Qin, D., M. A. Cagas, G. Ducanes, N. Magtibay-Ramos, and P. Quising (2008). Automatic leading indicators versus macroeconometric structural models: A comparison of inflation and GDP growth forecasting. *International Journal of Forecasting 24*, 399–413.

Ramanathan, R. (1995). *Introductory Econometrics*. Dryden Press/Harcourt Brace.

Sandberg, K. (2004). Growth of GRP in Chinese provinces. A test for spatial spillovers. ERSA conference papers, European Regional Science Association.

Sheng, Y. (2009). How globalized are the Chinese provinces? EAI Background Brief No. 423.

Stock, J. H. and M. W. Watson (1989). New indexes of coincident and leading economic indicators. In *NBER Macroeconomics Annual*, Volume 4.

Stock, J. H. and M. W. Watson (2005). Implications of dynamic factor models for VAR analysis. NBER Working Papers 11467, National Bureau of Economic Research, Inc.

World Bank (1994). China: Internal market development and regulation. a world bank country study.

Ying, L. G. (2003). Understanding China's recent growth experience: A spatial econometric perspective. *The Annals of Regional Science 37*(4), 613–628.

Young, A. (2000). The razor's edge: Distortions and incremental reform in the People's Republic of China. *The Quarterly Journal of Economics 115*(4), 1091–1135.

Appendix

Table 1: Descriptive statistics of the growth rates of real GDP of the Chinese provinces (%), 1979-2006

Region	Status	Coast	Interior	Minimum	Mean	Maximum	CV
Anhui	province		+	-0.9	10.9	21.0	0.49
Beijing	municipality	+		-1.5	10.6	17.5	0.34
Chongqing	municipality		+	4.7	10.2	16.2	0.30
Fujian	province	+		5.5	13.1	24.1	0.36
Gansu	province		+	-8.4	9.4	14.9	0.45
Guangdong	province	+		7.2	13.7	22.3	0.29
Guangxi	autonomous region	+		3.3	9.9	18.3	0.40
Guizhou	province		+	4.3	9.5	19.8	0.34
Hainan	province	+		1.8	11.5	40.2	0.63
Hebei	province	+		1.0	10.8	17.7	0.35
Heilongjiang	province		+	3.0	8.4	12.1	0.29
Henan	province		+	4.3	11.2	23.8	0.39
Hubei	province		+	4.5	10.7	20.9	0.37
Hunan	province		+	3.6	9.5	14.5	0.27
Jiangsu	province	+		2.5	12.8	25.6	0.36
Jiangxi	province		+	4.2	10.7	17.0	0.34
Jilin	province		+	-2.5	10.3	21.7	0.47
Liaoning	province	+		-1.6	9.6	16.8	0.44
Nei Mongol Zizhiqu	autonomous region		+	1.7	11.8	23.8	0.44
Ningxia	autonomous region		+	2.0	9.9	18.1	0.36
Qinghai	province		+	-9.1	8.5	17.8	0.59
Shaanxi	province		+	3.3	10.2	21.0	0.38
Shandong	province	+		4.0	12.2	21.9	0.32
Shanghai	municipality	+		3.0	10.3	14.9	0.33
Shanxi	province		+	0.8	9.9	21.6	0.46
Sichuan	province		+	2.6	9.8	14.2	0.29
Tianjin	municipality	+		1.6	10.6	19.3	0.39
Xinjiang Uygur	autonomous region		+	5.9	10.4	16.9	0.24
Xizang Zizhiqu	autonomous region		+	-9.2	10.1	25.3	0.74
Yunnan	province		+	3.1	9.7	16.0	0.31
Zhejiang	province	+		-0.6	13.3	22.0	0.37
Coast	group			-1.6	11.5	40.2	0.41
Interior	group			-9.2	10.1	25.3	0.42

Note: CV stands for coefficient of variation.

Sources: National Bureau of Statistics of China; Sheng (2009)

Table 2: Selected macroeconomic variables averaged by groups of Chinese provinces (%), 1992-2006

Variable	Coast	Interior
GDP growth	11.5	10.1
Trade-to-GRP	26.7	10.0
Exports-to-GRP	15.5	6.1
FDI-to-GRP	2.5	1.2

Table 3: Estimation results 1979 - 2007

	No spatial effects					Spatial effects											
						identical						group-specific					
	I_{OLS} minimum	I_{OLS} maximum	P_{OLS}	G_{OLS}	F_{OLS}	P^{SLM}_{MLE}	G^{SLM}_{MLE}	F^{SLM}_{MLE}	P^{SEM}_{MLE}	G^{SEM}_{MLE}	F^{SEM}_{MLE}	P^{SLM2}_{MLE}	G^{SLM2}_{MLE}	F^{SLM2}_{MLE}	P^{SEM2}_{MLE}	G^{SEM2}_{MLE}	F^{SEM2}_{MLE}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
$\widehat{\alpha}$	3.278	10.949	6.458			1.980			7.924			2.209			7.443		
	(2.1)	(4.7)	(19.0)			(5.1)			(17.6)			(5.7)			(16.8)		
$\widehat{\alpha}_1$				7.188			2.653			8.795			2.067			8.276	
				(14.7)			(6.1)			(17.3)			(3.7)			(17.1)	
$\widehat{\alpha}_2$				6.289			1.832			7.753			2.314			7.338	
				(18.8)			(4.8)			(17.2)			(4.7)			(16.6)	
$\widehat{\beta}$	-0.156	0.669	0.409	0.392	0.356	0.236	0.222	0.172	0.270	0.254	0.182	0.220	0.220	0.170	0.320	0.297	0.229
	(-1.1)	(4.1)	(11.9)	(11.4)	(11.6)	(8.8)	(8.2)	(6.4)	(8.4)	(7.9)	(5.5)	(8.2)	(8.2)	(6.4)	(10.2)	(9.4)	(7.1)
$\widehat{\rho}$						0.586	0.584	0.613									
						(19.0)	(18.9)	(20.5)									
$\widehat{\rho}_1$												0.628	0.639	0.669			
												(19.5)	(14.1)	(15.4)			
$\widehat{\rho}_2$												0.549	0.540	0.566			
												(17.0)	(12.9)	(13.8)			
$\widehat{\lambda}$									0.611	0.609	0.632						
									(19.2)	(19.2)	(20.7)						
$\widehat{\lambda}_1$															0.555	0.561	0.576
															(10.2)	(10.4)	(11.1)
$\widehat{\lambda}_2$															0.624	0.627	0.651
															(13.2)	(13.4)	(14.4)
R^2	0.001	0.394	0.172	0.182	0.206	0.411	0.418	0.439	0.412	0.420	0.408	0.423	0.423	0.415	0.382	0.396	0.380

Notes:

- $\widehat{\alpha}$, $\widehat{\alpha}_1$, and $\widehat{\alpha}_2$ denote the estimate of intercept for all provinces, Coastal provinces, and Interior provinces, respectively.
- $\widehat{\beta}$ denotes the estimate of the temporal autoregressive parameter.
- $\widehat{\rho}$, $\widehat{\rho}_1$, and $\widehat{\rho}_2$ denote the estimate of the spatial autoregressive parameter for all provinces, Coastal provinces, and Interior provinces, respectively.
- $\widehat{\lambda}$, $\widehat{\lambda}_1$, and $\widehat{\lambda}_2$ denote the estimate spatial error parameter for all provinces, Coastal provinces, and Interior provinces, respectively.
- number in brackets denotes the t-statistic

Table 4: Forecasting performance of models estimated using expanding window: RMSFE, 1989-2007

h-step ahead forecast	No spatial effects						Spatial effects											
							identical						group-specific					
	Naive 1	Naive 2	I_{OLS}	P_{OLS}	G_{OLS}	F_{OLS}	P^{SLM}_{MLE}	G^{SLM}_{MLE}	F^{SLM}_{MLE}	P^{SEM}_{MLE}	G^{SEM}_{MLE}	F^{SEM}_{MLE}	P^{SLM2}_{MLE}	G^{SLM2}_{MLE}	F^{SLM2}_{MLE}	P^{SEM2}_{MLE}	G^{SEM2}_{MLE}	F^{SEM2}_{MLE}
h=1	3.49	3.99	3.72	3.52	3.50	3.62	3.44	3.42	3.69	3.64	3.59	3.86	3.42	3.42	3.69	3.56	3.54	3.77
h=2	7.71	7.37	7.06	6.87	6.78	6.95	6.72	6.61	7.01	6.99	6.83	7.22	6.64	6.63	7.01	6.88	6.78	7.12
h=3	12.68	10.24	10.04	9.80	9.62	9.85	9.61	9.36	9.88	9.85	9.54	10.07	9.42	9.40	9.88	9.72	9.51	9.98
h=4	17.84	12.56	12.49	12.16	11.87	12.22	11.97	11.55	12.25	12.09	11.63	12.37	11.66	11.63	12.25	11.95	11.61	12.30
h=5	23.20	14.51	14.59	14.07	13.67	14.23	13.92	13.36	14.27	13.89	13.27	14.32	13.52	13.49	14.27	13.74	13.27	14.27
h=6	28.62	16.09	16.32	15.47	14.97	15.87	15.34	14.68	15.90	15.19	14.42	15.90	14.93	14.90	15.90	15.03	14.43	15.88
h=7	33.88	17.34	17.68	16.38	15.78	17.16	16.24	15.51	17.17	16.02	15.11	17.16	15.88	15.84	17.17	15.85	15.11	17.15
h=8	39.21	18.46	18.88	17.07	16.36	18.29	16.86	16.06	18.29	16.63	15.56	18.28	16.55	16.51	18.29	16.43	15.55	18.27
h=9	44.18	19.67	20.08	17.71	16.86	19.44	17.32	16.42	19.41	17.23	15.95	19.46	17.06	17.01	19.41	16.98	15.93	19.45
h=10	49.93	21.22	21.60	18.70	17.72	20.93	18.02	16.95	20.86	18.15	16.65	20.98	17.72	17.67	20.86	17.84	16.62	20.96
h=11	56.57	23.26	23.62	20.28	19.19	22.91	19.22	17.87	22.79	19.61	17.88	22.98	18.70	18.65	22.80	19.23	17.85	22.95
h=12	63.86	25.81	26.21	22.56	21.37	25.43	21.05	19.31	25.26	21.70	19.73	25.49	20.12	20.08	25.27	21.24	19.72	25.45
h=13	72.43	28.70	29.15	25.55	24.11	28.29	23.59	21.27	28.03	24.46	22.11	28.28	21.94	21.89	28.04	23.94	22.16	28.26
h=14	81.05	31.81	32.20	29.29	27.46	31.28	26.94	23.77	31.00	27.88	25.05	31.21	24.07	24.01	31.01	27.32	25.17	31.19
h=15	89.06	34.95	35.54	33.45	31.23	34.39	31.05	27.17	34.12	31.68	28.40	34.16	27.05	26.98	34.12	31.13	28.63	34.18

Total RMSFE = total root mean squared forecast errors (RMSFE) computed for all the provinces over all years together.
Relative RMSFE = total RMSFE of each alternative model divided by that of the benchmark model, for every forecasting horizon h.

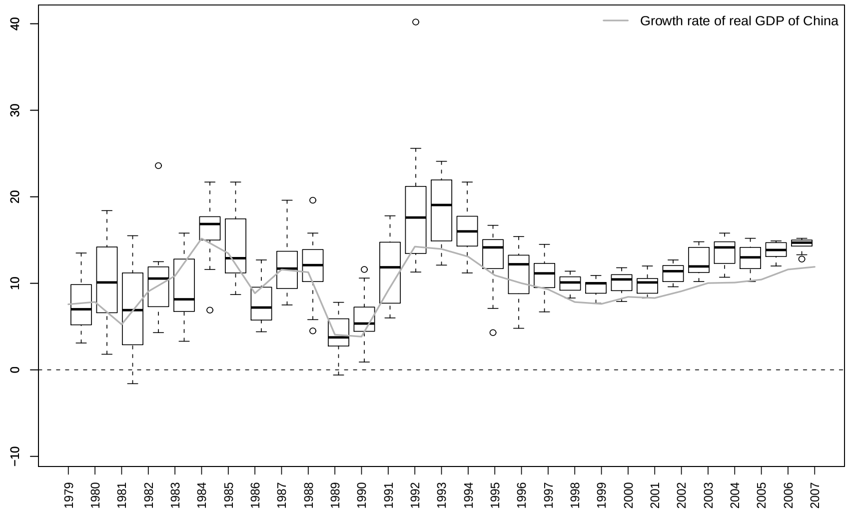
Table 5: Forecasting performance of models estimated using rolling 9-year window: RMSFE, 1989-2007

h-step	No spatial effects						Spatial effects											
ahead							identical						group-specific					
forecast	Naive 1	Naive 2	I_{OLS}	P_{OLS}	G_{OLS}	F_{OLS}	P^{SLM}_{MLE}	G^{SLM}_{MLE}	F^{SLM}_{MLE}	P^{SEM}_{MLE}	G^{SEM}_{MLE}	F^{SEM}_{MLE}	P^{SLM2}_{MLE}	G^{SLM2}_{MLE}	F^{SLM2}_{MLE}	P^{SEM2}_{MLE}	G^{SEM2}_{MLE}	F^{SEM2}_{MLE}
h=1	3.49	3.94	3.77	3.31	3.30	3.39	3.26	3.26	3.52	3.37	3.34	4.05	3.29	3.28	4.23	3.32	3.31	3.84
h=2	7.71	7.27	7.44	6.55	6.52	6.60	6.53	6.55	6.86	6.60	6.53	7.86	6.65	6.66	8.91	6.54	6.50	7.53
h=3	12.68	10.12	11.01	9.49	9.43	9.49	9.71	9.77	9.98	9.49	9.37	11.30	10.03	10.07	13.90	9.43	9.34	10.82
h=4	17.84	12.44	14.37	11.94	11.85	11.94	12.67	12.78	12.87	11.83	11.66	14.28	13.31	13.41	19.16	11.76	11.60	13.61
h=5	23.20	14.50	17.54	13.81	13.71	14.02	15.21	15.45	15.32	13.60	13.40	16.87	16.39	16.64	24.80	13.53	13.32	16.10
h=6	28.62	16.37	20.34	14.96	14.88	15.75	17.12	17.58	17.30	14.67	14.45	19.06	19.11	19.58	30.89	14.60	14.35	18.26
h=7	33.88	18.10	22.53	15.37	15.41	17.07	17.90	18.75	18.52	15.11	14.93	20.56	21.15	21.92	37.30	15.03	14.82	20.13
h=8	39.21	19.75	25.26	16.04	16.21	18.20	18.51	20.28	20.15	15.72	15.60	22.11	23.74	24.89	38.82	15.62	15.48	21.97
h=9	44.18	21.41	28.26	16.76	16.92	19.27	19.23	21.69	21.82	16.38	16.20	23.72	26.37	28.01	44.18	16.22	16.02	23.65
h=10	49.93	23.16	31.71	17.90	18.04	20.70	20.24	23.09	23.80	17.47	17.14	25.75	29.07	31.29	49.30	17.15	16.91	25.57
h=11	56.57	25.29	35.56	19.27	19.50	22.64	21.22	24.54	25.83	18.74	18.38	27.75	31.67	34.44	49.48	18.31	18.15	27.97
h=12	63.86	27.68	40.15	21.43	21.82	25.25	22.42	25.67	28.53	20.71	20.29	30.56	33.94	37.18	48.66	20.12	20.08	30.67
h=13	72.43	29.64	45.15	24.60	24.59	28.20	22.50	24.89	31.29	23.61	22.57	33.29	32.96	36.29	48.63	22.85	22.45	34.03
h=14	81.05	31.42	50.08	27.77	26.87	31.20	25.25	25.13	33.10	26.48	24.64	37.36	31.02	33.63	34.03	25.81	24.51	37.24
h=15	89.06	34.06	55.11	30.92	28.97	34.40	28.93	25.98	34.34	29.48	26.68	41.43	27.07	27.17	35.96	28.81	26.45	39.90

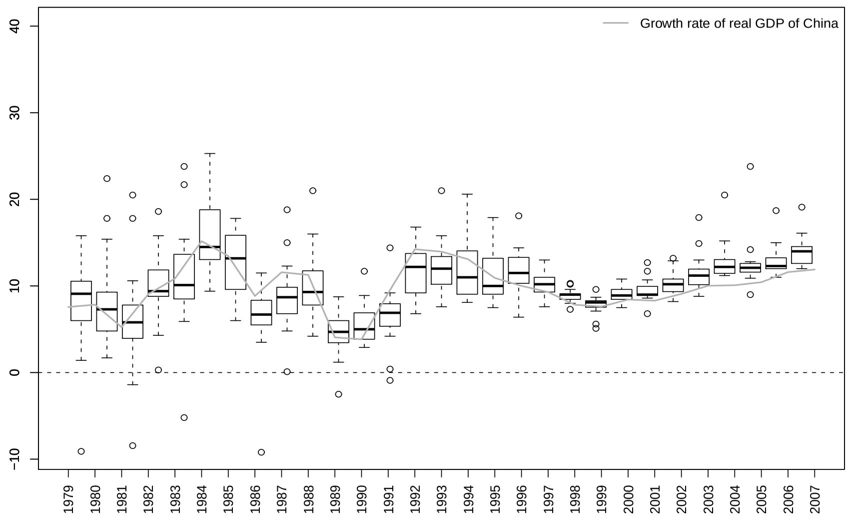
Total RMSFE = total root mean squared forecast errors (RMSFE) computed for all the provinces over all years together.
Relative RMSFE = total RMSFE of each alternative model divided by that of the benchmark model, for every forecasting horizon h.

Figure 1: Groups of Chinese provinces

Figure 2: Distribution of the growth rates of real GRP within groups of provinces, 1979-2007



(a) Coast provinces



(b) Interior provinces

Figure 3: Rolling RMSFE for 1-year horizon with 3-year window

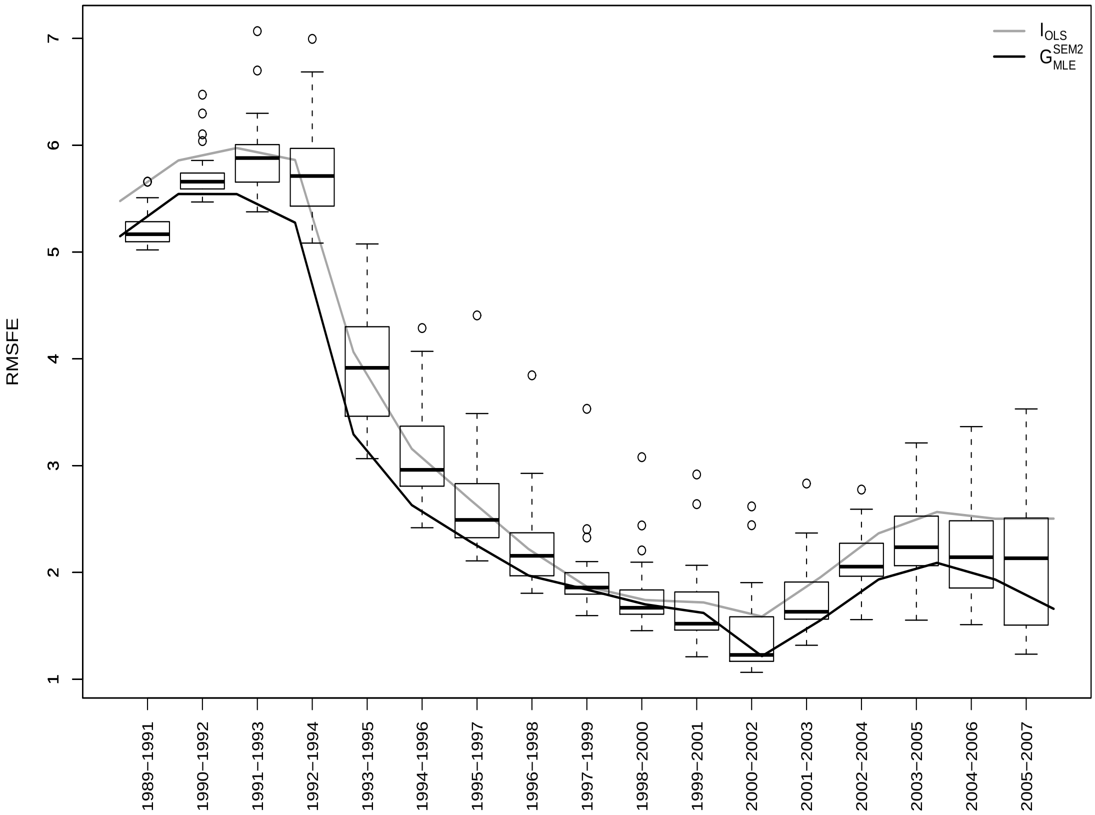


Figure 4: Rolling RMSFE for 5-year horizon with 3-year window

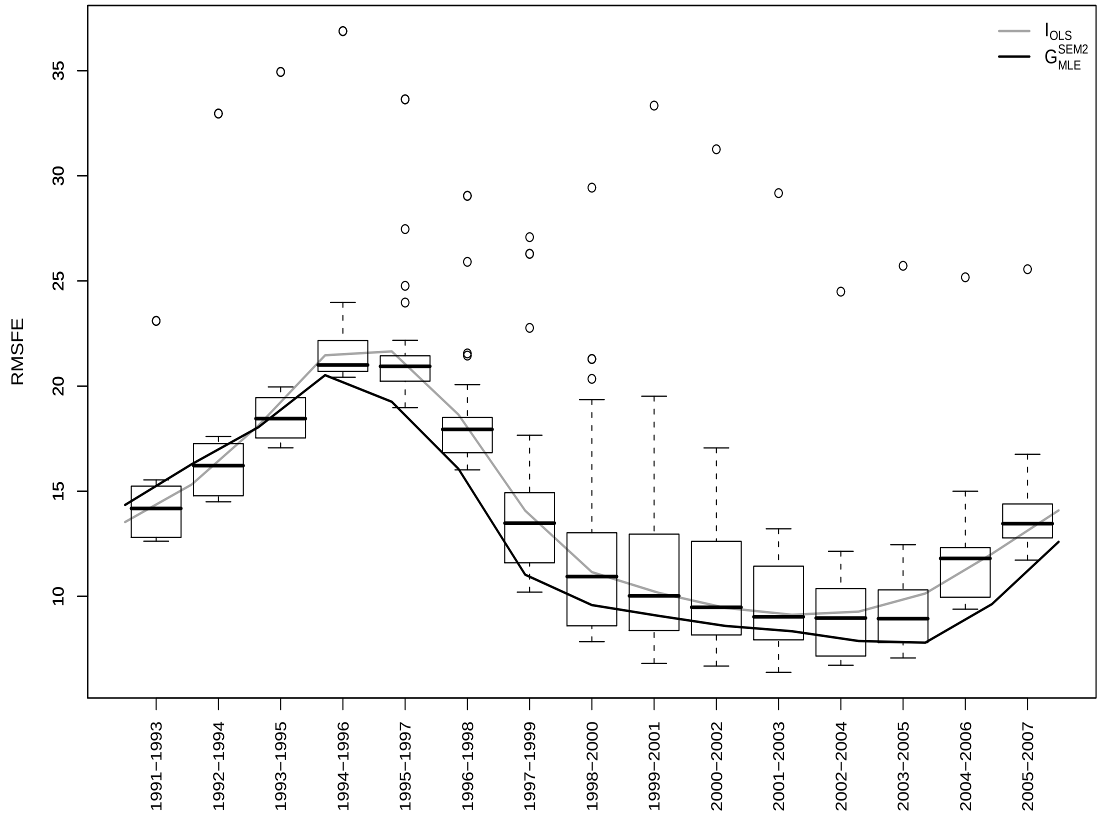


Figure 5: Rolling RMSFE for 10-year horizon with 3-year window