SPATIAL PANEL DATA ANALYSIS WITH FEASIBLE GLS TECHNIQUES: AN APPLICATION IN THE CHINESE REAL EXCHANGE RATE STUDIES*

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SUMMARY

Recent panel data approaches stress the importance of the location interdependence. Little has been done in the Balassa-Samuelson literature accounting for spatial dependence in the panel data context that allows for spatial autocorrelation. By utilizing the recently developed Kapoor et al. (2007) spatial panel feasible GLS methods, we find that the Balassa-Samuelson effect in the Chinese economy is more prominent with the black market exchange rate taken as a proxy of the real rate. The Dynamic Panel Data estimations based on the black market data provide stronger results in favour of accepting the theory.

Keywords: Panel data; Spatial econometrics; Error component; Real exchange rate

1. INTRODUCTION

Location or, in other words, spatial interactions are important determinants of economic activity. They could be due to competition, net work, spill-over, externalities, similar structures of economic activities and legislative issues etc. Ignoring these potentially omitted variables which have strong spatial elements

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in them might lead to errors in panel data regression models which are not independent but instead correlated across space.

According to Anselin (1988), a standard panel data set cannot be treated as independently generated due to the existence of similarities among areas that are close together. In fact, location issue have given rise to two major problems, spatial dependence and spatial heterogeneity, which causes loss of information and structural instability respectively (Anselin 1992). In the presence of spatial error autocorrelation, the OLS method would be inefficient and generate biased covariances. In addition, when the model contains spatially lagged dependent variable, the OLS estimators would also become biased. To overcome these problems, methods have been developed such as the maximum likelihood (ML) (see Anselin 1988; Anselin and Hudak 1992; Cliff and Ord 1973, 1981), generalized moments (GM) or instrumental variables (IV) (Kelejian and Prucha 1998, 1999), and feasible generalized least squares (FGLS) (Kapoor et al. 2007).

Following Anselin (1988), estimation of the fixed effects model can be carried out by ML that will yield consistent and unbiased estimators if the regularity condition of a likelihood function hold.[1] Estimation of the random effect model by ML is possible though complicated - the covariance matrix has unknown parameters which cannot be solved from the first-order conditions of the log-likelihood function; restrictions on unknown parameters cause difficulties for existing ML algorithms; existing algorithms that have solved these problems are often geared to simpler models without spatial effects (Elhorst 2001). Kelejian and Prucha (1999) argue that the ML method has substantial computational problems if the number of cross-sectional units

[1] The log-likelihood function must be demeaned.

is large.[2] They suggest that the IV estimator appears to be computationally feasible even for large sample size.[3] In their recent paper, Kapoor et al. (2007) propose an alternative method of the FGLS to estimate the random coefficient model extended to spatial and time-wise error autocorrelation, as well as heteroskedasticity.[4] The procedure starts with a linear panel model with spatially correlated random effects. The GM estimators for estimating the spatial autoregressive parameter and the variance components of the error process are established. They are used in correcting for spatial correlation in disturbances and in re-estimating the linear panel model in terms of the FGLS estimators. Finally, Kapoor et al. (2007) have shown that the true and feasible GLS estimators have the same large sample distribution. Thus, the FGLS is computationally feasible even in large sample.

This paper presents an empirical application of the recently developed spatial panel FGLS techniques by Kapoor et al. (2007) to the traditional Balassa-Samuelson literature.[5] We turn to a panel of 30 Chinese regions observed over 16 years as our sample. China is an interesting example that falls within our scope of study since many of its economic fundamentals are strongly spatial in nature. Table 1 shows a regional breakdown of growth rate in China in 1993 and 1999. The area of rapid growth is concentrated in costal areas, which share the border, and the areas without much growth are all the outlying areas, such as the west region.

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[2] In most spatial literature, a single cross-section is considered.

[3] Monte carlo results suggest that both the GMM and IV estimators are as efficient as the corresponding ML estimator in small sample (Das et al., 2003).

[4] However, the estimators might still be difficult to compute as they require matrix inversions whose orders may be large (Elhorst 2001).

[5] The main proposition of the Balassa-Samuelson effect (Balassa, 1964; Samuelson, 1964) is that high productivity growth of the tradable sector compared to non-tradable one leads to a rise in the relative price of non-tradable goods, which puts upward pressure on a country's real exchange rate.

Table 1. Spatial distribution of growth rate in China

Coastal region	1993	1999
Beijing	0.12	0.10
Tianjin	0.12	0.10
Hebei	0.18	0.09
Liaoning	0.15	0.08
Shanghai	0.15	0.10
Jiangsu	0.21	0.10
Zhejiang	0.22	0.10
Fujian	0.25	0.10
Shandong	0.19	0.10
Guangdong	0.22	0.10
Guangxi	0.21	0.08
Hainan	0.21	0.09
average growth	0.19	0.10
Central region		
Shanxi	0.12	0.05
Inner Mongolia	0.11	0.08
Jilin	0.13	0.08
Heilongjiang	0.08	0.08
Anhui	0.21	0.08
Jiangxi	0.14	0.08
Henan	0.16	0.08
Hubei	0.14	0.08
Hunan	0.13	0.08
average growth	0.13	0.08
West region		
Sichuan	0.14	0.06
Guizhou	0.10	0.08
Yunnan	0.11	0.07
Shaanxi	0.13	0.08
Gansu	0.12	0.08
Qinghai	0.10	0.08
Ningxia	0.10	0.09
Xinjiang	0.10	0.07
Tibet	0.08	0.10
average growth	0.11	0.08

Source. China Statistical Yearbook.

The empirical evidence we provide, based on two proxies of the real exchange rate, namely the Chinese official and black market rate,[6] suggest that the Balassa-Samuelson hypothesis seems to fare better when the black market rate is used. To complement our empirical spatial panel studies, we use Dynamic Panel Data methods(DPD)[7] in the application in order to see if the differences in the results are more a function of different techniques. The Dynamic Panel Data estimates based on the black market data also provide stronger confirmation of the theory.

Our study is organized in the following fashion. Section 2 discusses the panel data model based on the Kapoor et al. (2007) techniques that are used in the application. Section 3 describes the Balassa-Samuelson model that motivates our empirical tests. Section 4 presents the data and variable constructions. Section 5 summarizes our empirical evidence. Section 6 concludes the paper.

2. A FGLS ESTIMATION OF THE PANEL MODEL WITH SPATIALLY CORRELATED RANDOM EFFECTS

[6] China is an example where there exist frequent and complex changes in the exchange rate regimes. A fixed exchange rate regime co-existed with a flexible one during the period 1979 to 1993. A managed floating system has come into effect since 1994. The representative state rate throughout 1988 to 1993 was the market swap rate, which then unified with the official rate with the latter becoming the state rate instead. Under such circumstances, the ability to test for our theory might be hindered by the exchange rate data itself. To overcome these problems, we use the black market exchange rate as an additional proxy of the real rate in our analysis.

[7] We make use of the one- and two-step GMM (Arellano and Bond, 1991) and combined GMM estimations (Arellano and Bover, 1995; Blundell and Bond, 1998). Following Hall and Urga (1998), when time periods are short and the number of cross-sectional units is large, the GMM estimator is an efficient estimator, especially when taking the first differences or orthogonal deviations to eliminate the fixed effects.

This class of model was introduced by Kapoor et al. (2007). Such an approach allows one to consider random effects specifications assuming spatial and time-wise error autocorrelation. It represents the strand of spatial literature that is concerned with the error components. In particular, it focuses on the computation of the variance components of the error process in terms of the generalized moments procedures. The resultant FGLS estimators for the regression model are shown to be suitable in dealing with large samples.

The panel model with K parameters and J spatial units observed over the time periods $t = 1,...,T$ can be written as:

$$y_J = X_J\beta + \mu_J \qquad (1)$$

$$\mu_J = \rho(I_T \otimes W_J)\mu_J + \varepsilon_J\,, \quad |\rho| < 1 \qquad (2)$$

where:

1) X_J is a matrix of realizations on K time-varying explanatory variables assuming to be strictly exogenous; β is a vector of parameters; μ_J is a vector of unit specific errors; ρ is the spatial autoregressive parameter; W_J is a weighting matrix for the variables of each spatial unit.

2) The innovation process ε_J corresponds to an extension of the classical one-way error components model (Baltagi 2001). It is defined in order to allow itself to be correlated not just through the spatial units, but also over time: $\varepsilon_J = (e_T \otimes I_J)\mu_J + \nu_J$.

3) $y_J = [y'_J(1),...,y'_J(T)]'$; $X_J = [X'_J(1),...,X'_J(T)]'$;

$\mu_J = [\mu'_J(1),...,\mu'_J(T)]'$; $\nu_J = [\nu'_J(1),...,\nu'_J(T)]'$;

$E\mu_J = 0$; $E\mu_J\mu'_J = \sigma^2_\mu I_J$; $E\nu_J = 0$; $E\nu_J\nu'_J = \sigma^2_\nu I_{JT}$;

The estimators for estimating the spatial autoregressive parameter ρ and the variance components of the error term σ^2_ν and σ^2_μ,[8] are related as a system of six moment conditions:

$$\Gamma_J[\rho,\rho^2,\sigma^2_\nu,\sigma^2_1]' - \gamma_J = 0 \tag{3}$$

where:

$$\Gamma_J = \begin{bmatrix} \gamma^0_{11,J} & \gamma^0_{12,J} & \gamma^0_{13,J} & 0 \\ \gamma^0_{21,J} & \gamma^0_{22,J} & \gamma^0_{23,J} & 0 \\ \gamma^0_{31,J} & \gamma^0_{32,J} & \gamma^0_{33,J} & 0 \\ \gamma^1_{11,J} & \gamma^1_{12,J} & 0 & \gamma^1_{13,J} \\ \gamma^1_{21,J} & \gamma^1_{22,J} & 0 & \gamma^1_{23,J} \\ \gamma^1_{31,J} & \gamma^1_{32,J} & 0 & \gamma^1_{33,J} \end{bmatrix}; \qquad \gamma_J = \begin{bmatrix} \gamma^0_{1,J} \\ \gamma^0_{2,J} \\ \gamma^0_{3,J} \\ \gamma^1_{1,J} \\ \gamma^1_{2,J} \\ \gamma^1_{3,J} \end{bmatrix};$$

$$\gamma^h_{11,J} = \frac{2}{J(T-1)^{1-h}} E\mu'_J Q_{h,J}\overline{\mu}_J; \qquad \gamma^h_{12,J} = \frac{-1}{J(T-1)^{1-h}} E\overline{\mu}'_J Q_{h,J}\overline{\mu}_J;$$

$$\gamma^h_{13,J} = 1; \qquad \gamma^h_{21,J} = \frac{2}{J(T-1)^{1-h}} E\overline{\overline{\mu}}'_J Q_{h,J}\overline{\mu}_J;$$

$$\gamma^h_{22,J} = \frac{-1}{J(T-1)^{1-h}} E\overline{\overline{\mu}}'_J Q_{h,J}\overline{\overline{\mu}}_J; \qquad \gamma^h_{23,J} = \frac{1}{J} tr(W'_J W_J);$$

$$\gamma^h_{31,J} = \frac{1}{J(T-1)^{1-h}} E(\mu'_J Q_{h,J}\overline{\overline{\mu}}_J + \overline{\mu}'_J Q_{h,J}\overline{\mu}_J); \quad \gamma^h_{32,J} = \frac{-1}{J(T-1)^{1-h}} E\overline{\mu}'_J Q_{h,J}\overline{\overline{\mu}}_J;$$

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[8] Or, equivalently, σ^2_1, where $\sigma^2_1 = \sigma^2_\nu + T\sigma^2_\mu$, as T is fixed and $J \to \infty$.

$\gamma_{33,J}^{h} = 0$; $\quad \gamma_{1,J}^{h} = \frac{1}{J(T-1)^{1-h}} E\mu_J' Q_{h,J} \mu_J$;

$\gamma_{2,J}^{h} = \frac{-1}{J(T-1)^{1-h}} E\overline{\mu}_J' Q_{h,J} \overline{\mu}_J$; $\quad \gamma_{3,J}^{h} = \frac{1}{J(T-1)^{1-h}} E\mu_J' Q_{h,J} \overline{\mu}_J$;

$(h = 0,1)$.

On the basis of the first three sample moments in eq. (3), the initial GM estimators for ρ and σ_v^2, which are denoted by $\tilde{\rho}_J$ and $\tilde{\sigma}_{v,J}^2$, are defined as the unweighted[9] nonlinear least squares estimators, which minimize:

$$\left[g_J^0 - G_J^0 \begin{bmatrix} \rho \\ \rho^2 \\ \sigma_v^2 \end{bmatrix} \right]' \left[g_J^0 - G_J^0 \begin{bmatrix} \rho \\ \rho^2 \\ \sigma_v^2 \end{bmatrix} \right]$$

where:

$$G_J^0 = \begin{bmatrix} \frac{2}{J(T-1)} \hat{\mu}_J' Q_{0,J} \hat{\hat{\mu}}_J & -\frac{1}{J(T-1)} \hat{\hat{\mu}}_J' Q_{0,J} \hat{\hat{\mu}}_J & 1 \\ \frac{2}{J(T-1)} \hat{\hat{\mu}}_J' Q_{0,J} \hat{\hat{\hat{\mu}}}_J & -\frac{1}{J(T-1)} \hat{\hat{\hat{\mu}}}_J' Q_{0,J} \hat{\hat{\hat{\mu}}}_J & \frac{1}{J} Tr(W_J' W_J) \\ \frac{1}{J(T-1)} (\hat{\mu}_J' Q_{0,J} \hat{\hat{\hat{\mu}}}_J + \hat{\hat{\mu}}_J' Q_{0,J} \hat{\hat{\mu}}_J) & -\frac{1}{J(T-1)} \hat{\hat{\mu}}_J' Q_{0,J} \hat{\hat{\hat{\mu}}}_J & 0 \end{bmatrix};$$

$$g_J^0 = \begin{bmatrix} \frac{1}{J(T-1)} \hat{\mu}_J' Q_{0,J} \hat{\mu}_J \\ \frac{1}{J(T-1)} \hat{\hat{\mu}}_J' Q_{0,J} \hat{\hat{\mu}}_J \\ \frac{1}{J(T-1)} \hat{\mu}_J' Q_{0,J} \hat{\hat{\mu}}_J \end{bmatrix};$$

[9] Each of those moments carries equal weights.

$\hat{\mu}_J$ is the residuals generated by the OLS on model (1); $\hat{\bar{\mu}}_J = W_J \hat{\mu}_J$; $\hat{\bar{\bar{\mu}}}_J = W_J^2 \hat{\mu}_J$; $Q_{0,J}$ and $Q_{1,J}$ are defined in the paper.

And the initial estimator for σ_1^2, denoted by $\tilde{\sigma}_{1,J}^2$, corresponds to the fourth moment conditions in eq. (3), and is defined as:

$$\tilde{\sigma}_{1,J}^2 = \frac{1}{J}(\hat{\mu}_J - \tilde{\rho}_J \hat{\bar{\mu}}_J)' Q_{1,J} (\hat{\mu}_J - \tilde{\rho}_J \hat{\bar{\mu}}_J).$$

The weighted GM estimators for ρ, σ_v^2 and σ_1^2, depending on a user chosen level of weight to each sample moment, for instance, the partially weighted GM estimator $\breve{\rho}_J$, $\breve{\sigma}_{v,J}^2$ and $\breve{\sigma}_{1,J}^2$,[10] are defined as the minimizing value of:

$$\left[G_J \begin{bmatrix} \rho \\ \rho^2 \\ \sigma_v^2 \\ \sigma_1^2 \end{bmatrix} - g_J \right]' \tilde{r}_J^{-1} \left[G_J \begin{bmatrix} \rho \\ \rho^2 \\ \sigma_v^2 \\ \sigma_1^2 \end{bmatrix} - g_J \right]$$

where:

G_J

[10] The fully weighted GM estimator is based on all six moment conditions with the sample moments weighted by an approximation to the inverse of their variance covariance matrix.

$$
= \begin{bmatrix}
\frac{2}{J(T-1)}\hat{\mu}_J' Q_{0,J}\hat{\bar{\mu}}_J & -\frac{1}{J(T-1)}\hat{\bar{\mu}}_J' Q_{0,J}\hat{\bar{\mu}}_J & 1 & 0 \\
\frac{2}{J(T-1)}\hat{\bar{\bar{\mu}}}_J' Q_{0,J}\hat{\bar{\bar{\mu}}}_J & -\frac{1}{J(T-1)}\hat{\bar{\bar{\mu}}}_J' Q_{0,J}\hat{\bar{\bar{\mu}}}_J & \frac{1}{J}Tr(W_J'W_J) & 0 \\
\frac{1}{J(T-1)}(\hat{\mu}_J' Q_{0,J}\hat{\bar{\mu}}_J + \hat{\bar{\bar{\mu}}}_J' Q_{0,J}\hat{\bar{\bar{\mu}}}_J) & -\frac{1}{J(T-1)}\hat{\bar{\mu}}_J' Q_{0,J}\hat{\bar{\bar{\mu}}}_J & 0 & 0 \\
\frac{2}{J}\hat{\mu}_J' Q_{1,J}\hat{\bar{\mu}}_J & -\frac{1}{J}\hat{\bar{\mu}}_J' Q_{1,J}\hat{\bar{\mu}}_J & 0 & 1 \\
\frac{2}{J}\hat{\bar{\mu}}_J' Q_{1,J}\hat{\bar{\bar{\mu}}}_J & -\frac{1}{J}\hat{\bar{\bar{\mu}}}_J' Q_{1,J}\hat{\bar{\bar{\mu}}}_J & 0 & \frac{1}{J}Tr(W_J'W_J) \\
\frac{1}{J}(\hat{\mu}_J' Q_{1,J}\hat{\bar{\mu}}_J + \hat{\bar{\bar{\mu}}}_J' Q_{1,J}\hat{\bar{\bar{\mu}}}_J) & -\frac{1}{J}\hat{\bar{\mu}}_J' Q_{1,J}\hat{\bar{\bar{\mu}}}_J & 0 & 0
\end{bmatrix};
$$

$$
g_J = \begin{bmatrix}
\frac{1}{J(T-1)}\hat{\mu}_J' Q_{0,J}\hat{\mu}_J \\
\frac{1}{J(T-1)}\hat{\bar{\mu}}_J' Q_{0,J}\hat{\bar{\mu}}_J \\
\frac{1}{J(T-1)}\hat{\mu}_J' Q_{0,J}\hat{\bar{\mu}}_J \\
\frac{1}{J}\hat{\mu}_J' Q_{1,J}\hat{\mu}_J \\
\frac{1}{J}\hat{\bar{\mu}}_J' Q_{1,J}\hat{\bar{\mu}}_J \\
\frac{1}{J}\hat{\mu}_J' Q_{1,J}\hat{\bar{\mu}}_J
\end{bmatrix}; \qquad
\tilde{r}_J = \begin{bmatrix} \frac{1}{T-1}\tilde{\sigma}_{v,J}^4 & 0 \\ 0 & \tilde{\sigma}_{1,J}^4 \end{bmatrix} \otimes I_3 .
$$

The above procedures represent an enterprise such that each set of the GM estimators corresponds to specific weighting schemes for the moments. Next, Kapoor et al. (2007) use these GM estimators, correct for spatial correlation in disturbances, and re-estimate the linear panel model in terms of the FGLS estimators. The FGLS estimator is computed as the OLS estimator of eq. (1) after pre-multiplication of (1) with $[I_T \otimes (I_J - \breve{\rho}_J W_J)]$, and then $\breve{\sigma}_{v,J}\Omega_{\varepsilon,J}^{-1/2}(\breve{\sigma}_{v,J}^2, \breve{\sigma}_{1,J}^2)$.[11]

[11] The FGLS estimator is:

$$
\breve{\beta}_{FGLS} = \{X_J^{*}{}'(\breve{\rho}_J)[\Omega_{\varepsilon,J}^{-1}(\breve{\sigma}_{v,J}^2, \breve{\sigma}_{1,J}^2)]X_J^{*}(\breve{\rho}_J)\}^{-1} X_J^{*}{}'(\breve{\rho}_J)[\Omega_{\varepsilon,J}^{-1}(\breve{\sigma}_{v,J}^2, \breve{\sigma}_{1,J}^2)]y_J^{*}(\breve{\rho}_J)
$$

Kapoor et al. (2007) have established that generalization of the GM approach lead to consistent estimator of the parameter of the error process. The FGLS estimators based on those consistent estimators have been shown asymptotically equivalent to the true GLS, and thus consistent, asymptotically normal and computationally feasible in large samples.

3. THE BALASSA-SAMUELSON EFFECT

The foundations of productivity-based models of the real exchange rate, such as those of Balassa (1964) and Samuelson (1964), suggest that in fast growing countries, productivity growth in the tradable sector tends to be much higher than in the nontradable sector, and so the relative price of nontradables is expected to rise faster.[12] Combining this with the assumption that the prices of tradable goods are equalized across countries, the real currency appreciation of the country with high growth is derived. In the past forty years or so this proposition has been the leading principle for most real exchange rate studies.

The starting point for a formal representation of the Balassa-Samuelson model is the linkage between the real exchange rate and relative price of nontradable goods. Suppose that consumers spend a share α of their income on tradable goods (T) and a share (1-α) on nontradable goods (N). The price (P_t) is characterized by the constant-returns-to-scale Cobb-Douglas utility function, which takes the form of:

$P_t = (P_t^T)^{\alpha}(P_t^N)^{1-\alpha} = P_t^T\left(\frac{P_t^N}{P_t^T}\right)^{1-\alpha}$. Then, the real exchange rate (RER_t) reads as:

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[12] The intuition is as follows. If we assume that the nontradable sector is relatively more labour intensive, then an increase in tradadable sector productivity tends to raise the wages, and so the nontradable price must increase relatively more.

$$RER_t = \frac{XR_t P_t^*}{P_t} = XR_t \frac{P_t^{T^*}}{P_t^T} \frac{(\frac{P_t^{N^*}}{P_t^{T^*}})^{1-\alpha*}}{(\frac{P_t^N}{P_t^T})^{1-\alpha}}$$

, where XR_t denotes the nominal exchange rate; an asterisk represents the benchmark country.

Assuming $\alpha = \alpha^*$, and taking natural logarithms on both sides of the equation, we have:

$$\ln RER_t = (\ln XR_t + \ln P_t^{T^*} - \ln P_t^T) + (1-\alpha)[(\ln P_t^{N^*} - \ln P_t^{T^*}) - (\ln P_t^N - \ln P_t^T)]$$

As the Balassa-Samuelson hypothesis assumes that the Purchasing Power Parity (PPP) holds for tradable goods, then, for countries other than the benchmark country, the higher the relative price of nontradable goods, the higher the real exchange rate would become.

Note that in the Balassa-Samuelson model, it does not matter whether productivity disturbances are anticipated or unanticipated, since there is instantaneous factor mobility and the real rate is independent of aggregate demand factors. Thus, a perfectly anticipated trend productivity differential translates into a perfectly anticipated trend movement in the relative price of tradable goods (Rogoff 1992). Substituting out for relative prices yields:

$$\ln RER_t = (\ln XR_t + \ln P_t^{T^*} - \ln P_t^T) + (1-\alpha)[(\frac{\psi^{N^*}}{\psi^{T^*}})(\ln \theta_t^{T^*} - \ln \theta_t^{N^*}) - (\frac{\psi^N}{\psi^T})(\ln \theta_t^T - \ln \theta_t^N)],$$

where ψ is the labour share in a Cobb-Douglas production function; θ is the total factor productivity (TFP). If the first term follows I(0), then, home will experience real appreciation if its relative productivity in the tradable sector, which is $(\ln \theta_t^T - \ln \theta_t^N)$, is high relative to the one in the benchmark country, for which

$(\ln \theta_t^{T^*} - \ln \theta_t^{N^*})$ is given.[13]

In a schematic way, the following panel regression equations will motivate our empirical work:

$$\ln \frac{P_{jt}^N}{P_{jt}^T} = \lambda_1 + \tau_1 \ln \frac{\theta_{jt}^T}{\theta_{jt}^N} + \varepsilon_{jt};$$

$$\ln XR_{jt} = \lambda_2 + \tau_2 \ln \frac{P_{jt}^{T^*}}{P_{jt}^T} + \varepsilon_{jt};$$

$$\ln XRb_{jt} = \lambda_3 + \tau_3 \ln \frac{P_{jt}^{T^*}}{P_{jt}^T} + \varepsilon_{jt};$$

$$\ln RER_{jt} = \lambda_4 + \tau_4[(\ln P_{jt}^{N^*} - \ln P_{jt}^{T^*}) - (\ln P_{jt}^N - \ln P_{jt}^T)] + \varepsilon_{jt};$$

$$\ln RERb_{jt} = \lambda_5 + \tau_5[(\ln P_{jt}^{N^*} - \ln P_{jt}^{T^*}) - (\ln P_{jt}^N - \ln P_{jt}^T)] + \varepsilon_{jt};$$

$$\ln RER_{jt} = \lambda_6 + \tau_6[(\ln \theta_{jt}^{T^*} - \ln \theta_{jt}^{N^*}) - (\ln \theta_{jt}^T - \ln \theta_{jt}^N)] + \varepsilon_{jt};$$

$$\ln RERb_{jt} = \lambda_7 + \tau_7[(\ln \theta_{jt}^{T^*} - \ln \theta_{jt}^{N^*}) - (\ln \theta_{jt}^T - \ln \theta_{jt}^N)] + \varepsilon_{jt};$$

where a letter b denotes the black market; ε_{jt} is the error term; $j = 1,...,J, t = 1,...,T$.

4. DATA AND VARIABLE CONSTRUCTION

The empirical tests take into account the cross-sectional nature of the Balassa-Samuelson model for 30 Chinese regions. To do this, we turn to annual measures of Chinese inflation and industry input on regional and sectoral basis, for the period 1985 – 2000, which have been especially constructed for this work. Thus, the details

[13] Most researchers have assumed that the production functions in the tradable and nontradable sectors are the same, and so that the ψ s cancel each other out.

of the data and the construction of the empirical counterparts to the theoretical variables merit some discussion.

China is composed of twenty-two provinces (Anhui, Fujian, Gansu, Guangdong, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Jiangxi, Jilin, Liaoning, Qinghai, Shanxi, Shaanxi, Shandong, Sichuan, Yunnan, and Zhejiang), five autonomous regions (Guangxi, Inner Mongolia, Ningxia, Xinjiang, and Tibet), four municipalities (Beijing, Chongqing,[14] Shanghai, and Tianjin), and two special administrative regions (Hong Kong and Macau). Hong Kong and Macau are not within our scope of study due to different political and administrative systems compared to mainland China. The data for Chongqing have been integrated with those for Sichuan due to the lack of data before 1997. Thus, our sample consists of thirty regions.

We use the U.S. dollar as the numeraire currency since the U.S. is one of China's major trading partners. The nominal exchange rate is the annual average rate that is calculated based on monthly averages, in Chinese RMB yuan per U.S. dollar, from the IMF's *International Financial Statistics (IFS).* Following such a definition, a decrease in the nominal exchange rate implies appreciation. The black market exchange rate is calculated as an annual average based on end of month rate from the World Currency Yearbook and World Bank's *World Development Indicators (WDI).* The real exchange rate is defined as the bilateral real exchange rate between each region of China and the United States, adjusted to the difference in the GDP deflators of each region and the United States. The regional GDP deflator is the ratio of

[14] Chongqing was formerly (until 14 March 1997) a sub-provincial city within Sichuan province.

nominal to real GDP index (2000=1000)[15] for each region.

The prices of tradables and nontradables are proxied by the GDP deflator for the Chinese agriculture and industry, and for "other," which includes construction, transportation, storage, postal and telecommunications services, wholesale, retail trade and catering services.[16] These data are calculated as the ratio of the nominal to real GDP index,[17] both at 2000 constant prices for each sector and region. The relative price differential is calculated as the difference in the relative prices of each Chinese region and the United States.

The TFPs are computed as the Solow residuals using real GDP, capital stock, employment[18] and factor returns for each sector. Following China Statistical Yearbook (CSYB), the gross output value is the sum of the current value of final products produced in a given sector during a given period with the value of intermediate goods double counted. Due to the lack of data on sectoral capital stock, all total capital is approximated through investment,[19] except the one for industry

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[15] The real GDP index is obtained through the GDP index with the preceding year treated as 100.

[16] The tradable and nontradable categorization is on the basis of De Gregorio and Wolf (1994) criteria, which classify sectors on the basis of export shares in output for the whole sample of regions with a cut-off point of 10% to delineate nontradables.

[17] The sectoral GDP index (2000=100) is calculated through the real index of GDP (preceding year=100) in tradable and nontradable sectors, which is obtained using the fractions representing the composition of overall GDP and real GDP index by region and by individual sector.

[18] Due to the lack of data for labour hours, we follow most studies and use the total employment data as a proxy.

[19] Investment is the capital construction investment in "new projects, including construction of a new facility, or an addition to an existing facility, and the related activities of the enterprises, institutions or administrative units mainly for the purpose of expanding production activity, covering only projects each with a total investment of 500,000 RMB yuan and over" (CSYB).

from 1993 to 2002, which is available and refers to “the capital received by the industrial enterprises from investors that could be used as operational capitals for a long period” (CSYB). Total employment, according to the definition given by the CSYB, is “the number of staff and workers, which refers to a literal translation of the Chinese term ‘zhigong’ that includes employees of state-owned units in urban and rural areas (including government agencies), of collective-owned units in urban areas, of other ownership units in urban areas, and of state-collective joint ownership.” Wages necessary to the construction of factor returns are the total wage bills of staffs and workers, which are also drawn from CSYB.

On the basis of the current OECD’s *STructural ANalysis (STAN)* industry list, the De Gregorio and Wolf (1994) 10% threshold classifies the U.S. agriculture, hunting, forestry and fishing, mining and quarrying, total manufacturing, electricity, gas, and water supply sectors as tradables, and the remaining construction, wholesale and retail trade, restaurants and hotels, transport, storage, and communication sectors as nontradables. The U.S. tradable and nontradable price deflators are constructed by dividing the nominal value added by the real value added (2000=100) for each sector, as reported in OECD’s *Annual National Accounts – Main Aggregates* under the code VALU and VALUK respectively. The sectoral TFPs are computed using the real value added, capital stock, employment and factor returns for each sector. The capital stocks are proxied by gross domestic investment data, which are from the World Bank’s WDI. The employment and wage rate necessary to the construction of factor returns are drawn from the OECD’s STAN database under the code EMPN and WAGE respectively.

5. EMPIRICAL RESULTS

We apply the Kapoor et al. (2007) FGLS estimators to the Balassa-Samuelson framework, combined with the Dynamic Panel Data methods in our analysis. These empirical relevance of the long-run predictions is examined by utilizing the Chinese Regional Data. In particular, we use the Chinese black market exchange rate as an additional proxy of the real rate in our analysis since there have been frequent changes in the exchange rate regimes during our sample period 1985-2000.

5.1. Kapoor et al. (2007) Spatial Panel Data FGLS estimations

Table 2 contains the results from regressing relative price on relative productivity. There are three alternate FGLS estimators for estimating the regression equation, each corresponds to a chosen level of weight to each sample moment in eq. (3). The positive relationship between the two variables as implied by the theory is not well confirmed by the data - the FGLS estimator on relative productivity appears to be negative with an average magnitude of 0.03.

To test whether the PPP holds for tradable goods, we estimate the slope on the PPP exchange rate directly (see Table 3, 4). The coefficients generated by both initial and weighted GM estimation are highly significant, however, far from one. In terms of the black market rate – price relationship, they tend to be smaller, with an average magnitude of 0.16. Thus, the nominal and PPP exchange rates seem not to have a unitary theoretical relationship, which suggests that the PPP does not hold for tradable goods.

Next, we examine another key component of the Balassa-Samuelson hypothesis – the real exchange rate and relative price differential are negatively correlated. The results (see Table 5, 6) suggest a negative slope in both official and black market cases. On average, the slope estimate is -0.28 in the black market case, much greater than -0.20 in the official rate case in absolute value. Thus, the Balassa-Samuelson effect appears to be supported better by the black market rate.

Finally, following the theory, we would expect the coefficient on relative productivity differential to be negative since a fall of the real exchange rate implies an appreciation. The FGLS estimators (see Table 7, 8) based on the weighted GM procedures suggest the same results for the slope in the two exchange rate cases we consider, which are -0.03 under the partially weighted GM procedure, and -0.02 under the fully weighted one. However, the difference is that, when we look at the estimators generated by the initial GM estimation, the Balassa-Samuelson effect is more prominent when the black market rate is taken as a proxy of the real rate: the slope estimator is -0.01, as opposed to -0.004 in the official rate case.

The above analysis suggests that the price and productivity variables (as measured in the data) remain statistically insignificant in explaining the long-run cross region differences in the level of real exchange rates. We conclude by pointing out some limitation of our work on the empirical side, further work is required to develop a better quality panel database coving a longer time period and for a larger number of regions.

5.2. Dynamic Panel Data estimations

We estimate equations in levels, using one- and two-step GMM (Arellano and Bond, 1991) and combined GMM estimations (Arellano and Bover, 1995; Blundell and

Bond, 1998).[20] The standard errors and tests are based on the robust variance matrix. To select the proper lag length, we estimate equations with different combinations of the lag structure of the x_{jt} matrix. Among our experiments, we choose to look at the results where the residuals pass both the Sargan test[21] and AR(2) test, but fail the AR(1) test.[22]

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[20] The GMM estimation uses the instruments for transformed equations, whereas the combined GMM one uses the combination of instruments for both transformed and level equations.

[21] The dynamic panel data model is given by: $y_{jt} = \sum_{k=1}^{K} \alpha_k y_{j,t-k} + \beta'(L)x_{jt} + \lambda_t + \eta_j + v_{jt}$, $(j = 1,...,J, t = q+1,...,T_j)$, where α_k is the coefficient on lagged y_j, $\beta(L)$ is a vector of associated polynomials in the lag operator, x_{jt} is a $K \times 1$ vector of time-varying explanatory variables assumed to be strictly exogenous, λ_t is the time effect, η_j is the fixed individual effect, and v_{jt} is a vector of the independently and identically distributed errors, and q is the maximum lag length in the model.

The Sargan (1958, 1988) test tests the over-identifying restrictions. Define $A_J = (\frac{1}{J}\sum_{j=1}^{J} Z_j' H_j Z_j)^{-1}$, where Z_j is a matrix of instrumental variables; H_j is a weighting matrix. If A_J is optimal for any given Z_j, then under the null hypothesis that the instruments in Z are exogenous (i.e. uncorrelated with the individual effect η_j), the test statistic is $(\sum_{j=1}^{J} \hat{v}_j^{*}{}' Z_j) A_J (\sum_{j=1}^{J} Z_j' \hat{v}_j^{*}) \sim \chi_r^2$, where r represents the differences between the number of columns in Z and the number of columns in X.

[22] If the AR(1) model is mean-stationary, then Δy_{jt} will be uncorrelated with η_j, which suggests that $\Delta y_{j,t-1}$ can be used as instruments in the levels equations (see Arellano and Bover, 1995; Blundell and Bond, 1998)

When estimating the long-run relationship between relative price and relative productivity, we choose the results generated by one-step GMM regression with one lag on relative price and productivity (see left panel of Table 9), and by two-step combined GMM with one lag on relative price and productivity (see right panel of Table 9). Under such specifications of instruments in GMM estimators, the residuals pass all diagnostic tests well. We find that the positive relationship between the two variables is confirmed by the combined GMM regression, however, the coefficient remains statistically insignificant (p-value=0.37).

We follow the same lag selection procedure to estimate the slope on the PPP exchange rate. The slope coefficients, in the official rate – price relationship, remain significant throughout the two GMM regressions (see Table 10), however, far from one. They appear either non-unity ($\hat{\tau}_3 = 0.19$, see left panel of Table 11), or insignificant (p-value=0.30, see right panel of the same table) in the black market case, which suggest that the PPP hypothesis is not well supported by the data.

Tables 12 and 13 contain the dynamic panel results based on the real exchange rates and relative price differential. Regressions using the black market rate generate much more favourable results towards accepting the Balassa-Samuelson hypothesis – the slope coefficients (see Table 13) are statistically significant and have the expected signs. In contrast, in the official rate case (see Table 12), only the combined GMM regression shows a negative coefficient $(\hat{\tau}_4 = -0.12)$, which is consistent with the theory.

Finally, we examine the real exchange rate – relative productivity differential relationship. The black market rate performs well with the slope coefficients that are statistically significant and of the correct sign at the 5% level (see Table 15). The official rate, however, is shown to have a significant and positive relation with the relative productivity differential (see Table 14), which is inconsistent with the empirical regularities observed by the theory.

6. CONCLUSIONS

In this paper we investigate the relevance of the Balassa-Samuelson effect to the determination of regional inflation in China, taking account of spatial dependence in the panel data context that allows for spatial autocorrelation. The Balassa-Samuelson hypothesis seems to fare better with the Chinese black market exchange rate. The Dynamic Panel Data estimations based on the black market data, in comparing to its spatial panel regressions counterpart, provide stronger results towards accepting the Balassa-Samuelson theory. We conclude by pointing out some limitation of our work on the empirical side, further work is required to develop a higher quality database coving a longer period and for a larger panel of regions.

In China, the foreign exchange official and black market have co-existed for almost half a century with the latter being an important factor in economic activity (Phylaktis and Girardin 2001). One major reason why the black market exchange rate, as opposed to the official one, better reflects economic fundamentals, such as price and productivity, lies in the fact that the Chinese official rate is state – determined. Even in the recent floating period, the rate is merely allowed to fluctuate within a small range according to market forces. On the other hand, the black market rate is entirely market – determined, and so the band of fluctuation is much wider. The implication arising from our findings is that, in the presence of a large black market for foreign exchange, we may use the black market rate when carrying out economic studies since it moves more closely with economic fundamentals. Such a conclusion is important as it raises questions regarding the appropriate interpretations of the official exchange rate literature in some emerging economies.

TABLES

Table 2

Panel Data Estimation Assuming Spatially Correlated Errors

Relative Price and Relative Productivity

$$\ln\frac{P_{jt}^{N}}{P_{jt}^{T}} = \lambda_1 + \tau_1 \ln\frac{\theta_{jt}^{T}}{\theta_{jt}^{N}} + \varepsilon_{jt} \quad (j=1,...,J, t=1,...,T)$$

Initial GMM estimators		FGLS estimators	
$\tilde{\rho}_J$	0.26	Constant	0.13 (0.30)
$\tilde{\sigma}^2_{v,J}$	0.06	$\hat{\tau}_1$	-0.04 (0.24)
$\tilde{\sigma}^2_{1,J}$	0.59	σ^2	14.12
Partially weighted GMM estimators		**FGLS estimators**	
$\breve{\rho}_J$	0.13	Constant	0.06 (0.14)
$\breve{\sigma}^2_{v,J}$	0.05	$\hat{\tau}_1$	-0.03 (0.22)
$\breve{\sigma}^2_{1,J}$	0.39	σ^2	12.89
Fully weighted GMM estimators		**FGLS estimators**	
$\hat{\rho}_J$	0.14	Constant	0.07 (0.15)
$\hat{\sigma}^2_{v,J}$	0.04	$\hat{\tau}_1$	-0.03 (0.20)
$\hat{\sigma}^2_{1,J}$	0.57	σ^2	14.43

For spatial panel model: $y_J = X_J\beta + \mu_J$, $\mu_J = \rho(I_T \otimes W_J)\mu_J + (e_T \otimes I_J)\mu_J + v_J$, $\tilde{\rho}_J$, $\tilde{\sigma}^2_{v,J}$ and $\tilde{\sigma}^2_{1,J}$ are the initial GM estimators for the spatial autoregressive parameter ρ and variances of v_J and μ_J, respectively; $\breve{\rho}_J$, $\breve{\sigma}^2_{v,J}$ and $\breve{\sigma}^2_{1,J}$ are the partially weighted GM estimators for ρ and variances of v_J and μ_J; $\hat{\rho}_J$, $\hat{\sigma}^2_{v,J}$ and $\hat{\sigma}^2_{1,J}$ are the fully weighted GM estimators for ρ and variances of v_J and μ_J. Kapoor et al. (2007) use these GM estimators, which correspond to different weighting schemes for the sample moment, correct for spatial error correlations and re-estimate the panel model in terms of the FGLS. The figures in parentheses refer to the standard errors of the coefficients.

Table 3
Panel Data Estimation Assuming Spatially Correlated Errors
Official Exchange Rate and Relative Price of Tradable Goods

$$\ln XR_{jt} = \lambda_2 + \tau_2 \ln \frac{P_{jt}^{T^*}}{P_{jt}^{T}} + \varepsilon_{jt} \quad (j = 1,\ldots,J, t = 1,\ldots,T)$$

Initial GMM estimators		FGLS estimators	
$\tilde{\rho}_J$	0.25	Constant	2.11** (1.03)
$\tilde{\sigma}_{v,J}^2$	0.01	$\hat{\tau}_2$	0.34*** (0.10)
$\tilde{\sigma}_{1,J}^2$	0.09	σ^2	15.28
Partially weighted GMM estimators		**FGLS estimators**	
$\breve{\rho}_J$	0.14	Constant	2.09** (1.00)
$\breve{\sigma}_{v,J}^2$	0.01	$\hat{\tau}_2$	0.32*** (0.10)
$\breve{\sigma}_{1,J}^2$	0.06	σ^2	16.41
Fully weighted GMM estimators		**FGLS estimators**	
$\hat{\rho}_J$	0.13	Constant	2.10** (1.00)
$\hat{\sigma}_{v,J}^2$	0.01	$\hat{\tau}_2$	0.33*** (0.10)
$\hat{\sigma}_{1,J}^2$	0.09	σ^2	15.12

For spatial panel model: $y_J = X_J\beta + \mu_J$, $\mu_J = \rho(I_T \otimes W_J)\mu_J + (e_T \otimes I_J)\mu_J + v_J$, $\tilde{\rho}_J$, $\tilde{\sigma}_{v,J}^2$ and $\tilde{\sigma}_{1,J}^2$ are the initial GM estimators for the spatial autoregressive parameter ρ and variances of v_J and μ_J, respectively; $\breve{\rho}_J$, $\breve{\sigma}_{v,J}^2$ and $\breve{\sigma}_{1,J}^2$ are the partially weighted GM estimators for ρ and variances of v_J and μ_J; $\hat{\rho}_J$, $\hat{\sigma}_{v,J}^2$ and $\hat{\sigma}_{1,J}^2$ are the fully weighted GM estimators for ρ and variances of v_J and μ_J. Kapoor et al. (2007) use these GM estimators, which correspond to different weighting schemes for the sample moment, correct for spatial error correlations and re-estimate the panel model in terms of the FGLS. The figures in parentheses refer to the standard errors of the coefficients. Statistical significance at 5% and 0.2% levels are denoted by ** and *** respectively.

Table 4
Panel Data Estimation Assuming Spatially Correlated Errors
Black Market Exchange Rate and Relative Price of Tradable Goods

$$\ln XRb_{jt} = \lambda_3 + \tau_3 \ln \frac{P_{jt}^{T^*}}{P_{jt}^{T}} + \varepsilon_{jt} \quad (j = 1,...,J, t = 1,...,T)$$

Initial GMM estimators		FGLS estimators	
$\tilde{\rho}_J$	0.20	Constant	2.26† (1.50)
$\tilde{\sigma}^2_{v,J}$	0.01	$\hat{\tau}_3$	0.16* (0.10)
$\tilde{\sigma}^2_{1,J}$	0.03	σ^2	16.73
Partially weighted GMM estimators		**FGLS estimators**	
$\breve{\rho}_J$	0.17	Constant	2.25† (1.50)
$\breve{\sigma}^2_{v,J}$	0.01	$\hat{\tau}_3$	0.15† (0.10)
$\breve{\sigma}^2_{1,J}$	0.02	σ^2	16.08
Fully weighted GMM estimators		**FGLS estimators**	
$\hat{\rho}_J$	0.17	Constant	2.26† (1.50)
$\hat{\sigma}^2_{v,J}$	0.01	$\hat{\tau}_3$	0.16* (0.10)
$\hat{\sigma}^2_{1,J}$	0.04	σ^2	15.44

For spatial panel model: $y_J = X_J\beta + \mu_J$, $\mu_J = \rho(I_T \otimes W_J)\mu_J + (e_T \otimes I_J)\mu_J + v_J$, $\tilde{\rho}_J$, $\tilde{\sigma}^2_{v,J}$ and $\tilde{\sigma}^2_{1,J}$ are the initial GM estimators for the spatial autoregressive parameter ρ and variances of v_J and μ_J, respectively; $\breve{\rho}_J$, $\breve{\sigma}^2_{v,J}$ and $\breve{\sigma}^2_{1,J}$ are the partially weighted GM estimators for ρ and variances of v_J and μ_J; $\hat{\rho}_J$, $\hat{\sigma}^2_{v,J}$ and $\hat{\sigma}^2_{1,J}$ are the fully weighted GM estimators for ρ and variances of v_J and μ_J. Kapoor et al. (2007) use these GM estimators, which correspond to different weighting schemes for the sample moment, correct for spatial error correlations and re-estimate the panel model in terms of the FGLS. The figures in parentheses refer to the standard errors of the coefficients. Statistical significance at 10% and 20% levels are denoted by * and † respectively.

Table 5
Panel Data Estimation Assuming Spatially Correlated Errors
Real Exchange Rate and Relative Price Differential

$$\ln RER_{jt} = \lambda_4 + \tau_4[(\ln P_{jt}^{N^*} - \ln P_{jt}^{T^*}) - (\ln P_{jt}^{N} - \ln P_{jt}^{T})] + \varepsilon_{jt}$$

$$(j = 1,...,J, t = 1,...,T)$$

Initial GMM estimators		FGLS estimators	
$\tilde{\rho}_J$	0.24	Constant	2.60 (2.21)
$\tilde{\sigma}^2_{v,J}$	0.05	$\hat{\tau}_4$	-0.24 (0.22)
$\tilde{\sigma}^2_{1,J}$	0.28	σ^2	12.56
Partially weighted GMM estimators		**FGLS estimators**	
$\breve{\rho}_J$	0.15	Constant	2.66 (2.22)
$\breve{\sigma}^2_{v,J}$	0.04	$\hat{\tau}_4$	-0.18 (0.20)
$\breve{\sigma}^2_{1,J}$	0.19	σ^2	14.54
Fully weighted GMM estimators		**FGLS estimators**	
$\hat{\rho}_J$	0.15	Constant	2.66 (2.22)
$\hat{\sigma}^2_{v,J}$	0.04	$\hat{\tau}_4$	-0.18 (0.20)
$\hat{\sigma}^2_{1,J}$	0.29	σ^2	14.28

For spatial panel model: $y_J = X_J\beta + \mu_J$, $\mu_J = \rho(I_T \otimes W_J)\mu_J + (e_T \otimes I_J)\mu_J + v_J$, $\tilde{\rho}_J$, $\tilde{\sigma}^2_{v,J}$ and $\tilde{\sigma}^2_{1,J}$ are the initial GM estimators for the spatial autoregressive parameter ρ and variances of v_J and μ_J, respectively; $\breve{\rho}_J$, $\breve{\sigma}^2_{v,J}$ and $\breve{\sigma}^2_{1,J}$ are the partially weighted GM estimators for ρ and variances of v_J and μ_J; $\hat{\rho}_J$, $\hat{\sigma}^2_{v,J}$ and $\hat{\sigma}^2_{1,J}$ are the fully weighted GM estimators for ρ and variances of v_J and μ_J. Kapoor et al. (2007) use these GM estimators, which correspond to different weighting schemes for the sample moment, correct for spatial error correlations and re-estimate the panel model in terms of the FGLS. The figures in parentheses refer to the standard errors of the coefficients.

Table 6

Panel Data Estimation Assuming Spatially Correlated Errors

Real Parallel Exchange Rate and Relative Price Differential

$$\ln RERb_{jt} = \lambda_5 + \tau_5[(\ln P_{jt}^{N^*} - \ln P_{jt}^{T^*}) - (\ln P_{jt}^{N} - \ln P_{jt}^{T})] + \varepsilon_{jt}$$

$$(j = 1,...,J, t = 1,...,T)$$

Initial GMM estimators		FGLS estimators	
$\tilde{\rho}_J$	0.22	Constant	2.92 (2.53)
$\tilde{\sigma}^2_{v,J}$	0.08	$\hat{\tau}_5$	-0.31 (0.28)
$\tilde{\sigma}^2_{1,J}$	0.44	σ^2	11.82
Partially weighted GMM estimators		**FGLS estimators**	
$\breve{\rho}_J$	0.16	Constant	2.97 (2.55)
$\breve{\sigma}^2_{v,J}$	0.07	$\hat{\tau}_5$	-0.27 (0.26)
$\breve{\sigma}^2_{1,J}$	0.32	σ^2	12.68
Fully weighted GMM estimators		**FGLS estimators**	
$\hat{\rho}_J$	0.16	Constant	2.97 (2.54)
$\hat{\sigma}^2_{v,J}$	0.06	$\hat{\tau}_5$	-0.27 (0.24)
$\hat{\sigma}^2_{1,J}$	0.49	σ^2	12.99

For spatial panel model: $y_J = X_J\beta + \mu_J$, $\mu_J = \rho(I_T \otimes W_J)\mu_J + (e_T \otimes I_J)\mu_J + v_J$, $\tilde{\rho}_J$, $\tilde{\sigma}^2_{v,J}$ and $\tilde{\sigma}^2_{1,J}$ are the initial GM estimators for the spatial autoregressive parameter ρ and variances of v_J and μ_J, respectively; $\breve{\rho}_J$, $\breve{\sigma}^2_{v,J}$ and $\breve{\sigma}^2_{1,J}$ are the partially weighted GM estimators for ρ and variances of v_J and μ_J; $\hat{\rho}_J$, $\hat{\sigma}^2_{v,J}$ and $\hat{\sigma}^2_{1,J}$ are the fully weighted GM estimators for ρ and variances of v_J and μ_J. Kapoor et al. (2007) use these GM estimators, which correspond to different weighting schemes for the sample moment, correct for spatial error correlations and re-estimate the panel model in terms of the FGLS. The figures in parentheses refer to the standard errors of the coefficients.

Table 7
Panel Data Estimation Assuming Spatially Correlated Errors
Real Exchange Rate and Relative Productivity Differential

$$\ln RER_{jt} = \lambda_6 + \tau_6[(\ln\theta_{jt}^{T^*} - \ln\theta_{jt}^{N^*}) - (\ln\theta_{jt}^{T} - \ln\theta_{jt}^{N})] + \varepsilon_{jt}$$

$$(j = 1,...,J, t = 1,...,T)$$

Initial GMM estimators		FGLS estimators	
$\tilde{\rho}_J$	0.22	Constant	2.65 (3.00)
$\tilde{\sigma}_{v,J}^2$	0.03	$\hat{\tau}_6$	-0.004 (0.17)
$\tilde{\sigma}_{1,J}^2$	0.14	σ^2	17.84
Partially weighted GMM estimators		**FGLS estimators**	
$\breve{\rho}_J$	0.17	Constant	2.55 (2.78)
$\breve{\sigma}_{v,J}^2$	0.03	$\hat{\tau}_6$	-0.03 (0.17)
$\breve{\sigma}_{1,J}^2$	0.08	σ^2	19.19
Fully weighted GMM estimators		**FGLS estimators**	
$\hat{\rho}_J$	0.16	Constant	2.59 (2.80)
$\hat{\sigma}_{v,J}^2$	0.03	$\hat{\tau}_6$	-0.02 (0.17)
$\hat{\sigma}_{1,J}^2$	0.15	σ^2	16.98

For spatial panel model: $y_J = X_J\beta + \mu_J$, $\mu_J = \rho(I_T \otimes W_J)\mu_J + (e_T \otimes I_J)\mu_J + v_J$,

$\tilde{\rho}_J$, $\tilde{\sigma}_{v,J}^2$ and $\tilde{\sigma}_{1,J}^2$ are the initial GM estimators for the spatial autoregressive parameter ρ and variances of v_J and μ_J, respectively; $\breve{\rho}_J$, $\breve{\sigma}_{v,J}^2$ and $\breve{\sigma}_{1,J}^2$ are the partially weighted GM estimators for ρ and variances of v_J and μ_J; $\hat{\rho}_J$, $\hat{\sigma}_{v,J}^2$ and $\hat{\sigma}_{1,J}^2$ are the fully weighted GM estimators for ρ and variances of v_J and μ_J. Kapoor et al. (2007) use these GM estimators, which correspond to different weighting schemes for the sample moment, correct for spatial error correlations and re-estimate the panel model in terms of the FGLS. The figures in parentheses refer to the standard errors of the coefficients.

Table 8
Panel Data Estimation Assuming Spatially Correlated Errors
Real Parallel Exchange Rate and Relative Productivity Differential

$$\ln RERb_{jt} = \lambda_7 + \tau_7[(\ln\theta_{jt}^{T^*} - \ln\theta_{jt}^{N^*}) - (\ln\theta_{jt}^{T} - \ln\theta_{jt}^{N})] + \varepsilon_{jt}$$

$$(j = 1,...,J, t = 1,...,T)$$

Initial GMM estimators		FGLS estimators	
$\tilde{\rho}_J$	0.20	Constant	2.99 (2.50)
$\tilde{\sigma}_{v,J}^2$	0.05	$\hat{\tau}_7$	-0.01 (0.22)
$\tilde{\sigma}_{1,J}^2$	0.15	σ^2	18.82
Partially weighted GMM estimators		**FGLS estimators**	
$\breve{\rho}_J$	0.18	Constant	2.88 (2.40)
$\breve{\sigma}_{v,J}^2$	0.04	$\hat{\tau}_7$	-0.03 (0.20)
$\breve{\sigma}_{1,J}^2$	0.09	σ^2	19.28
Fully weighted GMM estimators		**FGLS estimators**	
$\hat{\rho}_J$	0.17	Constant	2.96 (2.50)
$\hat{\sigma}_{v,J}^2$	0.05	$\hat{\tau}_7$	-0.02 (0.22)
$\hat{\sigma}_{1,J}^2$	0.16	σ^2	17.09

For spatial panel model: $y_J = X_J\beta + \mu_J$, $\mu_J = \rho(I_T \otimes W_J)\mu_J + (e_T \otimes I_J)\mu_J + v_J$, $\tilde{\rho}_J$, $\tilde{\sigma}_{v,J}^2$ and $\tilde{\sigma}_{1,J}^2$ are the initial GM estimators for the spatial autoregressive parameter ρ and variances of v_J and μ_J, respectively; $\breve{\rho}_J$, $\breve{\sigma}_{v,J}^2$ and $\breve{\sigma}_{1,J}^2$ are the partially weighted GM estimators for ρ and variances of v_J and μ_J; $\hat{\rho}_J$, $\hat{\sigma}_{v,J}^2$ and $\hat{\sigma}_{1,J}^2$ are the fully weighted GM estimators for ρ and variances of v_J and μ_J. Kapoor et al. (2007) use these GM estimators, which correspond to different weighting schemes for the sample moment, correct for spatial error correlations and re-estimate the panel model in terms of the FGLS. The figures in parentheses refer to the standard errors of the coefficients.

Table 9

Dynamic Panel Data Estimation

Relative Price and Relative Productivity

$$\ln \frac{P_{jt}^{N}}{P_{jt}^{T}} = \lambda_1 + \tau_1 \ln \frac{\theta_{jt}^{T}}{\theta_{jt}^{N}} + \varepsilon_{jt} \quad (j = 1,...,J, t = 1,...,T)$$

Coefficient	Equation (1)	Lags	Coefficient	Equation (1)	Lags
$\hat{\tau}_1$ †	-0.05 (0.16)	1	$\hat{\tau}_1$ ††	0.03 (0.37)	1
Constant	-0.07 (0.21)		Constant	-0.01 (0.44)	
Trend	-		Trend	-	
1 or 2-step GMM	1-step		1 or 2-step combined GMM	2-step	
Transformation used	1st differences		Transformation used	1st differences	
Wald (joint)	198.00** (0.00)		Wald (joint)	131.40** (0.00)	
Wald (dummy)	695.00** (0.00)		Wald (dummy)	0.61 (0.44)	
Sargan test	117.0 (0.18)		Sargan test	29.04 (1.00)	
AR(1) test	-3.95** (0.00)		AR(1) test	-3.21** (0.00)	
AR(2) test	0.55 (0.58)		AR(2) test	0.58 (0.56)	

† The GMM estimation uses the instruments for transformed equations; †† The GMM estimation uses the combination of instruments for both transformed and level equations; The figures in parentheses refer to p-values; Statistical significance at 5% and 10% levels are denoted by ** and * respectively.

Table 10

Dynamic Panel Data Estimation

Official Exchange Rate and Relative Price of Tradable Goods

$$\ln XR_{jt} = \lambda_2 + \tau_2 \ln \frac{P_{jt}^{T^*}}{P_{jt}^{T}} + \varepsilon_{jt} \quad (j = 1,...,J, t = 1,...,T)$$

Coefficient	Equation (2)	Lags	Coefficient	Equation (2)	Lags
$\hat{\tau}_2$ †	0.35** (0.00)	3	$\hat{\tau}_2$ ††	0.40** (0.02)	1
Constant	0.05** (0.00)		Constant	1.08** (0.00)	
Trend	-		Trend	-	
1 or 2-step GMM	2-step		1 or 2-step combined GMM	2-step	
Transformation used	Orthogonal deviations		Transformation used	1st differences	
Wald (joint)	1993.00** (0.00)		Wald (joint)	9100.00** (0.00)	
Wald (dummy)	35.90** (0.00)		Wald (dummy)	55.48** (0.00)	
Sargan test	29.98 (1.00)		Sargan test	30.00 (1.00)	
AR(1) test	-5.00** (0.00)		AR(1) test	-4.54** (0.00)	
AR(2) test	1.20 (0.23)		AR(2) test	-0.99 (0.32)	

† The GMM estimation uses the instruments for transformed equations; †† The GMM estimation uses the combination of instruments for both transformed and level equations; The figures in parentheses refer to p-values; Statistical significance at 5% and 10% levels are denoted by ** and * respectively.

Table 11
Dynamic Panel Data Estimation
Black Market Exchange Rate and Relative Price of Tradable Goods

$$\ln XRb_{jt} = \lambda_3 + \tau_3 \ln \frac{P_{jt}^{T^*}}{P_{jt}^{T}} + \varepsilon_{jt} \quad (j = 1,\ldots,J, t = 1,\ldots,T)$$

Coefficient	Equation (2)	Lags	Coefficient	Equation (1)	Lags
$\hat{\tau}_3$ †	0.19** (0.01)	4	$\hat{\tau}_3$ ††	0.09 (0.30)	3
Constant	0.03** (0.03)		Constant	1.37** (0.00)	
Trend	-		Trend	-	
1 or 2-step GMM	2-step		1 or 2-step combined GMM	2-step	
Transformation used	1st differences		Transformation used	None	
Wald (joint)	3897.00** (0.00)		Wald (joint)	1.55e+005** (0.00)	
Wald (dummy)	4.63** (0.03)		Wald (dummy)	8.90e+004** (0.00)	
Sargan test	29.75 (1.00)		Sargan test	30.00 (1.00)	
AR(1) test	-5.27** (0.00)		AR(1) test	-5.15** (0.00)	
AR(2) test	-1.73* (0.08)		AR(2) test	-0.96 (0.34)	

† The GMM estimation uses the instruments for transformed equations; †† The GMM estimation uses the combination of instruments for both transformed and level equations; The figures in parentheses refer to p-values; Statistical significance at 5% and 10% levels are denoted by ** and * respectively.

Table 12

Dynamic Panel Data Estimation

Real Exchange Rate and Relative Price Differential

$$\ln RER_{jt} = \lambda_4 + \tau_4[(\ln P_{jt}^{N^*} - \ln P_{jt}^{T^*}) - (\ln P_{jt}^{N} - \ln P_{jt}^{T})] + \varepsilon_{jt}$$

$$(j = 1,...,J, t = 1,...,T)$$

Coefficient	Equation (2)	Lags	Coefficient	Equation (2)	Lags
$\hat{\tau}_4$ †	0.08*	1	$\hat{\tau}_4$ ††	-0.12**	1
	(0.08)			(0.04)	
Constant	-0.05**		Constant	0.28**	
	(0.00)			(0.00)	
Trend	-		Trend	-	
1 or 2-step GMM	2-step		1 or 2-step combined GMM	2-step	
Transformation used	1st differences		Transformation used	1st differences	
Wald (joint)	205.60**		Wald (joint)	2909.00**	
	(0.00)			(0.00)	
Wald (dummy)	44.52**		Wald (dummy)	15.34**	
	(0.00)			(0.00)	
Sargan test	29.95		Sargan test	29.94	
	(1.00)			(1.00)	
AR(1) test	-3.64**		AR(1) test	-3.83**	
	(0.00)			(0.00)	
AR(2) test	-0.29		AR(2) test	-0.07	
	(0.77)			(0.94)	

† The GMM estimation uses the instruments for transformed equations; †† The GMM estimation uses the combination of instruments for both transformed and level equations; The figures in parentheses refer to p-values; Statistical significance at 5% and 10% levels are denoted by ** and * respectively.

Table 13
Dynamic Panel Data Estimation
Real Parallel Exchange Rate and Relative Price Differential

$$\ln RERb_{jt} = \lambda_5 + \tau_5[(\ln P_{jt}^{N^*} - \ln P_{jt}^{T^*}) - (\ln P_{jt}^{N} - \ln P_{jt}^{T})] + \varepsilon_{jt}$$

$$(j = 1,...,J, t = 1,...,T)$$

Coefficient	Equation (2)	Lags	Coefficient	Equation (1)	Lags
$\hat{\tau}_5$ †	-0.44** (0.00)	3	$\hat{\tau}_5$ ††	-0.48** (0.00)	1
Constant	0.05** (0.00)		Constant	0.25** (0.00)	
Trend	-		Trend	-	
1 or 2-step GMM	2-step		1 or 2-step combined GMM	2-step	
Transformation used	Orthogonal deviations		Transformation used	None	
Wald (joint)	2165.00** (0.00)		Wald (joint)	4496.00** (0.00)	
Wald (dummy)	16.23** (0.00)		Wald (dummy)	(33.13)** (0.00)	
Sargan test	29.81 (1.00)		Sargan test	29.98 (1.00)	
AR(1) test	-3.52** (0.00)		AR(1) test	4.10** (0.00)	
AR(2) test	-1.81* (0.07)		AR(2) test	-0.17 (0.87)	

† The GMM estimation uses the instruments for transformed equations; †† The GMM estimation uses the combination of instruments for both transformed and level equations; The figures in parentheses refer to p-values; Statistical significance at 5% and 10% levels are denoted by ** and * respectively.

Table 14
Dynamic Panel Data Estimation
Real Exchange Rate and Relative Productivity Differential

$$\ln RER_{jt} = \lambda_6 + \tau_6[(\ln\theta_{jt}^{T^*} - \ln\theta_{jt}^{N^*}) - (\ln\theta_{jt}^{T} - \ln\theta_{jt}^{N})] + \varepsilon_{jt}$$

$$(j = 1,...,J, t = 1,...,T)$$

Coefficient	Equation (1)	Lags	Coefficient	Equation (1)	Lags
$\hat{\tau}_6$ †	0.09**	1	$\hat{\tau}_6$ ††	0.11**	1
	(0.00)			(0.00)	
Constant	-0.04**		Constant	-0.06	
	(0.00)			(0.56)	
Trend	-		Trend	-	
1 or 2-step GMM	2-step		1 or 2-step combined GMM	2-step	
Transformation used	1st differences		Transformation used	Orthogonal deviations	
Wald (joint)	249.70**		Wald (joint)	2153.00**	
	(0.00)			(0.00)	
Wald (dummy)	79.38**		Wald (dummy)	0.35	
	(0.00)			(0.56)	
Sargan test	29.96		Sargan test	29.97	
	(1.00)			(1.00)	
AR(1) test	-3.56**		AR(1) test	-3.83**	
	(0.00)			(0.00)	
AR(2) test	0.11		AR(2) test	0.43	
	(0.91)			(0.67)	

† The GMM estimation uses the instruments for transformed equations; †† The GMM estimation uses the combination of instruments for both transformed and level equations; The figures in parentheses refer to p-values; Statistical significance at 5% and 10% levels are denoted by ** and * respectively.

Table 15

Dynamic Panel Data Estimation

Real Parallel Exchange Rate and Relative Productivity Differential

$$\ln RERb_{jt} = \lambda_7 + \tau_7[(\ln\theta_{jt}^{T^*} - \ln\theta_{jt}^{N^*}) - (\ln\theta_{jt}^{T} - \ln\theta_{jt}^{N})] + \varepsilon_{jt}$$

$$(j = 1,...,J, t = 1,...,T)$$

Coefficient	Equation (1)	Lags	Coefficient	Equation (1)	Lags
$\hat{\tau}_7$ †	-0.14** (0.00)	3	$\hat{\tau}_7$ ††	-0.13** (0.00)	2
Constant	0.09** (0.00)		Constant	-1.15** (0.00)	
Trend	-		Trend	-	
1 or 2-step GMM	2-step		1 or 2-step combined GMM	2-step	
Transformation used	Orthogonal deviations		Transformation used	Orthogonal deviations	
Wald (joint)	1291.00** (0.00)		Wald (joint)	3065.00** (0.00)	
Wald (dummy)	36.22** (0.00)		Wald (dummy)	16.55** (0.00)	
Sargan test	29.95 (1.00)		Sargan test	29.87 (1.00)	
AR(1) test	-3.58** (0.00)		AR(1) test	-3.46** (0.00)	
AR(2) test	-1.53 (0.13)		AR(2) test	0.35 (0.73)	

† The GMM estimation uses the instruments for transformed equations; †† The GMM estimation uses the combination of instruments for both transformed and level equations; The figures in parentheses refer to p-values; Statistical significance at 5% and 10% levels are denoted by ** and * respectively.

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