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A Global Cointegration Approach

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Selin Özyurt and Timo Mitze[1]

The Spatial Dimension of Trade- and FDI-driven Productivity Growth in Chinese Provinces – A Global Cointegration Approach

Abstract

Since the introduction of its "open door" policy in the late 1970s, China has been attracting a growing share of FDI inflows and its international trade integration has advanced considerably. In this study, we take a closer look at the regional growth impact of the Chinese internationalization activity on labour productivity over the period 1979-2006. Our empirical analysis thereby extends the existing empirical literature by considering the likely spatial effects associated with Trade- and FDI-led growth in a dynamic error correction modelling framework. Our results indicate that, in the long-run relationship, regional labour productivity is indeed driven by direct and indirect spatial effects of FDI and trade activity next to further supply side factors such as the regional infrastructure equipment and human capital endowment. Similarly, in the short-run, changes in FDI activity and especially human capital variables are found to matter for the regional growth dynamics.

JEL Classification: O11, O18, P20, R10

Keywords: Trade; FDI; productivity growth; spatial spillovers; China

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1 Selin Ozyurt: European Central Bank; Timo Mitze: RWI and Ruhr-Universität Bochum. *– The authors would like to thank Luc Anselin, Rosina Moreno, Sylvie Démurger, Xiaolan Fu as well as Christoph M. Schmidt for their suggestions and constructive remarks on this research. – This Working Paper should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.* *– All correspondence to: Timo Mitze, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, E-Mail: timo.mitze@rwi-essen.de.*

1. Introduction

Since the introduction of the economic reform policy in the late 1970s, China has undergone a continuous and spectacular economic growth process. China's impressive economic take-off has been also accompanied by the rapid expansion of its foreign trade and foreign capital inflows. Along with China's economic rise, it has become an important topic of interest to investigate the advantages of being a "global player". Generally speaking, academics and policy-makers perceive long-term foreign investment and export activity as the key drivers of economic growth in emerging market economies (EMEs). On the one hand, in capital-scarce economies, foreign direct investment (FDI) and trade represent an effective way to accumulate capital and create employment opportunities. On the other hand, the affiliates of multinational companies in emerging economies are generally found to be more productive and more integrated in international production networks than their domestic counterparts (Du *et al.* 2011). In the course of time, advanced technologies brought by MNCs can potentially diffuse to the local economy through various channels such as imitation-demonstration and contagion effects, competition of foreign firms, training of local employees, backward and forward linkages and trade.[3]

Despite this general belief in the benefits of openness, the empirical literature has – surprisingly – reported mixed evidence on the existence of positive spillovers via FDI and foreign trade in emerging economies (Aitken and Harrison 1999, Haddad and Harrison 1993). For instance, from a microeconomic point of view, fierce competition arising from the entry of MNCs is a detrimental factor, which could potentially crowd out the less efficient domestic firms (Kokko 1996). Moreover, the entry of multinational companies, which typically pay a wage premium, may bring about increasing labour costs for domestic firms in competitive markets. As for productivity spillovers generated by openness to trade and FDI, empirical studies highlight that their occurrence is not automatic and it is essentially conditioned on host country's innovation and absorptive capabilities. True, a large technology gap between local and foreign firms can indicate a big "catch-up" potential; however, it can also hint at the poor absorptive capabilities of the local partners (Blomström and Sjöholm 1999).

[3] We present a short literature overview dealing with the various transmission channels of technology diffusion by MNCs in the appendix (see Box A.1).

The availability of adequate human capital (Xu 2000, Borensztein *et al.*1998) and basic infrastructure facilities (Blomström and Wolff 1994) are found to be crucial in fostering the absorption of advanced technologies from MNCs.

Taking up these research questions, in this paper we investigate empirically the trade-FDI and productivity nexus for 30 Chinese provinces over the period 1979-2006. We believe that China's emergence as a major global partner over the last three decades illustrates a perfect case study. Prior to 1979, China was an isolated economy where foreign trade and FDI were virtually nonexistent. Since 1979, the country has progressively moved away from being an autarchic economy towards a market-oriented one. China's opening up to the world came along with very fast and sustainable economic growth. Over the last few years China's current economic growth model has been largely criticized for being unsustainable because of its excessive reliance on factor accumulation. Yet, according to neoclassical theory, only productivity-driven economic growth is sustainable in the long run. On that account, understanding the main dynamics behind China's economic rise is very crucial. We consider that China portrays a unique observational study to explore the long-term relationship between openness to the world and productivity increase in emerging economies.

China is a very large country, characterized by heterogeneous space and striking economic disparities between regions and between urban and rural areas. In addition, China's internal economic geography has been greatly influenced by the political reforms, globalization and trade liberalization over the past decades (Fujita and Hu, 2001). Yet, recent regional productivity analyses on China (e.g., Jiang 2011, Yang and Lahr 2010) generally fail to exploit the distinctive characteristics of geographical data. By considering each region as an isolated and independent identity, they overlook regional dynamics, agglomeration and proximity effects. It has been widely asserted by regional scientists, however, that ignoring spatial effects introduced by cross-sectional information could generate serious misspecification problems and lead to questionable parameter estimates and statistical inferences (Abreu *et al*. 2005).

Over the last decade, an increasing number of studies started to incorporate the spatial dimension to analyse mainstream questions in international economics. To name only a few, Coughlin and Segev (2000) and Blonigen *et al.* (2007) highlight the importance of agglomeration economies in FDI location decisions respectively in China and in the OECD countries, In the same way, Özyurt and Daumal (2011) find strong spatial spillovers arising from export performances of micro-regions in Brazil. Keller and Shuie (2007) investigate the expansion of inter-regional trade networks in China trough spatial explanatory data analysis and detect significant spatial interactions among provinces. Ying (2003) conducts a spatial analysis on Chinese output growth and reveals that previous studies which ignore spatial dependence generate unreliable results due to misspecification issues. Yet, these spatial econometric applications are essentially confined to the cross-sectional dimension and the integration of time dimension to spatial econometric analysis mostly remains a challenge ahead for researchers.[4]

This study aims at improving our understanding of the dynamics behind China's productivity performance over the last three decades and extends on the above mentioned literature by using the novel concept of global cointegration that allows assessing the role played by spatial spillover effects in a dynamic space-time data setting. To the best of our knowledge, this work is the first to investigate the impact of openness on productivity from a spatio-temporal perspective which combines long- and short-run information. We strongly believe that the simultaneous inclusion of the space-time dimension in a unified cointegration modelling scheme generates a wealth of information that could be used to draw further policy recommendations.

The remainder of the paper proceeds as follows. Section 2 sketches our empirical modelling strategy based on the global cointegration approach. Section 3 discusses the underlying data and presents some stylized facts of Chinese regional economic development. The empirical findings are presented and interpreted in Section 4 and Section 5 concludes the paper.

[4] Non-spatial panel data approaches to assess the role of inter-regional output and FDI spillovers are, for instance, conducted by Groenewold et al. (2007). By using a VAR technique the authors show that coastal regions are a source of strong spillover effects to the central and western regions.

2. Empirical Modelling Framework

In this section, we take up the arguments raised above to set up a modelling framework which allows an empirical assessment of the role played by trade and FDI on economic growth. Besides modelling the direct impacts, we also put special attention to the role played by spatial spillovers in output determination. Moreover, we try to dismantle the different long- and short-run influencing factors in a dynamic modelling approach.

A common point of departure in the literature is to start from a stylized regional production function to model the transmission channels from trade and FDI activity to economic growth (see also Edwards 1998). A spatially extended version is, for instance, presented in Ertur and Koch (2007). A fairly general stylized model can be written as

$$(1) \qquad Y_{i,t} = A_{i,t} K_{i,t}^{\alpha} \tilde{K}_{i,t}^{\varphi} Z_{1i,t}^{\beta_1} \cdots Z_{mi,t}^{\beta_m} \cdots \tilde{Z}_{1i,t}^{\delta_1} \cdots \tilde{Z}_{mi,t}^{\delta_m} L_{i,t}^{\phi} \tilde{L}_{i,t}^{\lambda}$$

where $Y_{i,t}$ denotes the output measure of region i at time t. The cross-sectional dimension is specified as $i=1,\ldots,N$ and the time dimension is $t=1,\ldots,T$. K and L are capital and labor inputs, respectively. Variables denoted by "~" indicate weighted averages of values for spatial proximate neighbors (spatial lags). The Z_1 to Z_m variables and their associated spatial lags indicate further private and public inputs in the production function such as infrastructure equipment, human capital endowment as well as trade and FDI activity. $A_{i,t}$ is the total factor productivity (TFP) of region i, which is driven by two effects (Bode et al., 2009): One term, which represents the productivity effects of time-invariant location factors (proxied by fixed effects ι_i) as well as a second term to measure interregional productivity spillovers $\left(\tilde{A}_{i,t}\right)$.

The so-called spatial lag term for a variable X defined below in eq.(2) is constructed as a weighted average of values in neighbouring regions, where w_{ij} are the individual weights taken from a spatial weighting matrix $\boldsymbol{W}$. The latter is typically row-standardized with $\sum_j w_{ij} = 1$. Alternative empirical operationalizations for $\boldsymbol{W}$ are discussed in Section 3.

(2) $$\tilde{X}_{i,t} = \sum_{j \neq i}^{N} w_{ij} X_{j,t} \ ,$$

Besides modelling the particular long-run level of output as outlined in eq.(1), we are further interested in tracking the short-run growth performance among Chinese provinces. This may give additional insights with respect to the dynamic adjustment processes taking place within and between regions. We do so by using a cointegration approach, which allows simultaneously modelling a relationship among variables in levels and growth rates (see Engle and Granger 1987). The main advantage of the cointegration approach to economic analysis is that it avoids the risk of running a spurious regression, even if the underlying variables are non stationary and integrated of order *I(1)* or higher.

A necessary condition for cointegration analysis is that the variables in focus co-move over time. Hence, if the error term $u_{i,t}$ for a (log-linear) regression of $y_{i,t} = \lambda x_{i,t} + u_{i,t}$ is stationary and integrated of order *I(0)*, then the two variables y and x are said to form a stable cointegration relationship. Using the information contained in $u_{i,t} = y_{i,t} - \lambda x_{i,t}$ we can then extend the long-run cointegration regression to a dynamic Error Correction Model (ECM) of the form $\Delta y_{i,t} = \phi u_{i,t-1} + b \Delta x_{i,t} + e_{i,t}$. The latter equation describes the dynamic adjustment process of the dependent variable in first-differences (defined for a log-transformed variable as $\Delta y_{i,t} = [y_{i,t} - y_{i,t-1}]$) towards its long-run equilibrium, where ϕ and b are the regression coefficients for the short-run specification.

As recently outlined by Beenstock and Felsenstein (2010), the concept of cointegration and error correction can be extended in order to explicitly account for a spatial dimension by including spatial lags of the endogenous variables and the set of regressors both in the long-run equation as well as the dynamic ECM. On the one hand, the resulting Spatial Error Correction Model (SpECM) allows us to control for spatial autocorrelation and thus ensures well-behaved *i.i.d.* residuals. Moreover, the authors argue that the inclusion of spatial lags may have important implications for the existence of a stable cointegration relationship among variables, especially if their co-movement is not solely driven by the time variation within each panel observation (that is for each cross-section separately), but for also by the between panel variation. The latter channel assumes, for instance, that the spatial lag for a certain regressor such as FDI activity in the geographical neighborhood is cointegrated with the output level (y) of the ith region in focus.

Therefore, the SpECM concept may encompass three important types of cointegration: (i) if cointegration only applies within spatial units but not between them, we refer to "local" cointegration. The latter is the standard concept of cointegration with respect to (panel) time series analysis. (ii) "spatial" cointegration refers to the case in which non-stationary variables are cointegrated over time between spatial units but not within them.[5] (iii) Finally, if nonstationary spatial panel data are both cointegrated within and between cross-sections over time, we refer to "global" cointegration.

For the production function approach in eq.(1) we may thus specify a SpECM of the following form[6]

$$\begin{aligned} \Delta y_{i,t} &= c + \iota_i + \eta_1 \Delta \tilde{y}_{i,t} + \eta_2 \Delta k_{i,t} + \eta_3 \Delta \tilde{k}_{i,t} \\ &+ \eta_4 \Delta l_{i,t} + \eta_5 \Delta \tilde{l}_{i,t} + \eta_6 ' \Delta \mathbf{z}_{i,t} + \eta_7 ' \Delta \tilde{\mathbf{z}}_{i,t} \\ &+ \phi_1 u_{i,t-1} + \phi_2 \tilde{u}_{i,t-1} + e_{i,t}, \end{aligned} \tag{3}$$

and

$$u_{i,t} = y_{i,t} - c - \iota_i - \psi_1 \tilde{y}_{i,t} - \psi_2 k_{i,t} - \psi_3 \tilde{k}_{i,t} - \psi_4 l_{i,t} - \psi_5 \tilde{l}_{i,t} - \psi_6 ' \mathbf{z}_{i,t} - \psi_7 ' \tilde{\mathbf{z}}_{i,t} . \tag{4}$$

In eq.(3) and eq.(4), we introduce the vector $\mathbf{z}$ as $\mathbf{z}=(z_1,\ldots, z_m)$; $\eta_1,\ldots,\eta_7$ are the coefficients of the first differenced variables (and their spatial lags), ϕ_1 *and* ϕ_2 are the coefficients of from $u_{i,t}$ and $\tilde{u}_{i,t}$ as the (spatially weighted) residuals from the long-term relationships of the system in eq.(4). ϕ_1 *and* ϕ_2 can be interpreted as error correction coefficients, which drive the system to its long-run equilibrium state. Global error correction arises if the coefficients of these EC-terms are non-zero. For the nested case of "local" error correction we assume that $\phi_1<0$. The same holds for the alternative case of "spatial" error correction in ϕ_2. The residuals in the dynamic short-run equation ($e_{i,t}$) are assumed to be temporally and spatially uncorrelated. Finally one has to note that in the short run, any regressor may affect Δy differently from how it affects y in the long run equation.

[5] As Beenstock & Felsenstein (2010) point out, in this case, the long-term trends in spatial units are mutually determined and do not depend upon developments within spatial units.
[6] Small letters indicate that the variables are transformed by logarithms.

Since both eq.(3) and eq.(4) take the form of a spatial Durbin model, incorporating spatial lags of the endogenous and exogenous variables, an appropriate estimation strategy is to use maximum likelihood (ML) techniques. For panel data settings, Beer and Riedl (2009) have recently proposed an ML-estimator for the spatial Durbin model in a fixed effects setting, which makes use of a (generalized Helmert) transformation proposed by Lee and Yu (2010) in order to eliminate the fixed effects (ι_i) from the regression equations.[7] The authors show by means of a Monte Carlo simulation experiment that this SDM-ML estimator has satisfactory small-sample properties. We apply this estimator in the following.

3. Data and Stylized Facts

3.1. Data

In the empirical analysis of productivity, we use a panel data set of 30 Chinese provinces over the period 1979-2006.[8] The underlying data are originated from various issues of the China Statistical Yearbook and all nominal values are deflated by using region-specific retail price indexes. In the following regression analyses, the dependent variable is labour productivity measured in terms of value added per employee *(lprod)*.

FDI and trade openness are the main regressors of interest of this study. FDI is measured by foreign capital actually utilized per employee while trade openness *(trade)* is defined as the sum of exports and imports as share of GDP. Capital intensity *(capital)* refers to the average level of capital assets per employee. This variable aims at capturing labour productivity gains stemming from capital deepening. In the theoretical and empirical literature, human capital and infrastructure development are found to be very robust determinants of host economies' absorptive capabilities. In this study, we include two alternative measures of human capital; basic education *(basic edu)* which corresponds to the number of primary schools per inhabitant whereas higher education *(high edu)* is the share of the population studying at the institutions of higher education. Intuitively, we expect the diffusion of advanced

[7] The standard time mean operator cannot be used in spatial model settings since the disturbances of the model would be serially correlated over time (see Lee and Yu, 2010).
[8] Tibet is excluded from the panel data set due to data unavailability.

technologies to be determined by the availability of a highly educated workforce while basic education could be linked to productivity in manufacturing sector (which generally has lower value added content). We measure physical infrastructure facilities *(infra)* by the combined length of highways and railways (per 10000 square km of provincial area). The variable *state* is the share of the state sector in total employment and it controls for potential inefficiencies arising from the oversized state sector in some regions. For the empirical estimation all variables are transformed into logarithms. Descriptive statistics of the variables are given in Table 1.

<<< Table 1 about here >>>

In order to estimate the SpECM model outlined in section 2, we also need an empirical approximation of the underlying spatial structure. The spatial weighting matrix (***W***) provides the structure of the assumed spatial relationships and captures the strength of potential spatial interactions between observations. The determination of an accurate spatial weights matrix is a fundamental step in spatial data analysis. In the literature, spatial weights can be defined in a number of alternative ways:

- **Simple contiguity matrix:** It is a binary matrix is based on the adjacency of location of observations. Put w_{ij} to express the magnitude of the interaction between province i and j. If two provinces share a common boundary we put $w_{ij}=1$ and $w_{ij}=0$ otherwise.
- **Distance based contiguity:** In distance based contiguity matrices, spatial weights attributed to the observations depend on the geographic or Euclidean distance d_{ij} between locations i and j. Distance matrices differ in the functional form used. Inverse function of distance [$w_{ij} =1/d_{ij}$] or inverse distance raised to some power N with [$w_{ij} =1/d_{ij}^N$] are commonly used in the literature.

In this study, we use the row-standardized binary contiguity matrix as default option. The latter has recently been shown to perform better in terms of a higher probability of detecting the true model with lower mean squared errors of the parameter set compared to distance based weighting matrices (Stakhovych and Bijmolt 2009). To check the robustness of our results we alternatively use an inverted distance-based weighting matrix. Before moving to the empirical estimation, we present some stylized facts on the evolution of openness and productivity in Chinese regions over time.

3.2. Stylized Facts

As pointed out before, China started to receive foreign capital in 1979 along with the implementation of the economic reform policies. However, the economic transition of China has been a gradual and spatially uneven process. During the early stages of the economic reform, FDI flows to China amounted fairly low and they were confined to a few selected regions. Four Special Economic Zones (SEZ) have been established on the southern part of Guangdong and Fujian provinces, to attract foreign investors by offering preferential financial and fiscal treatments. In 1984, the SEZ were extended to further 14 coastal cities and to Hainan Island. In 1992, the historical tour of the Chinese leader Deng Xiaoping to coastal southern cities emphasized the commitment to open door policy and started a new era for China's integration into the world economy.

After 1992, a progressive switch from particular regimes to nationwide opening up policies has emerged. Therefore, the coordination of regional development and reduction of inequalities between inland and coastal regions became priority objectives in the 8th and 9th five-year plans (1991-2000). Since the 1990s, continuous support has been provided to western and inland regions to ensure a more even distribution of foreign capital. In line with this initiative, the Western Development Strategy was launched in 1999 to establish a favorable business environment in western China through the development of human capital, natural resources, transport and communication infrastructures and so on (Özyurt and Guironnet 2011).

Along with the market oriented economic reforms to attract long-term foreign capital, Chinese government also implemented preferential policies to encourage export activity (e.g. duty exemptions for imports of intermediate goods used in export-oriented production). In addition, China's accession into the WTO in 2001 contributed to reduce trade distortions and reinforced its integration in global markets. In 2009, China overtook Germany to become world's largest exporter and since mid 2000s it is the second largest recipient of foreign direct investment in the world (following the US).

In China, FDI patterns show a great disparity regarding the distribution between regions and sectors. Until the last decade, China's economic reforms and open door policy have essentially focused on the development of coastal regions. That is to say, preferential treatment of coastal regions brought about uneven opening up paths and generated serious income disparities among regions. Aside from preferential policies, coastal regions in China also enjoy a number of growth-enhancing structural advantages such as geographical proximity to international markets, low information costs, better infrastructural development, superior access to sea-routes and a relatively well educated human capital stock. Therefore, despite the growing share of the inland regions, today the bulk of FDI inflows and export activity remain concentrated in coastal regions (see Figure 1). These internal dynamics of China in terms of economic geography already indicates the necessity to take into account the spatial interactions to explain the productivity, FDI and Trade dynamics.

<<< Figure 1 about here >>>

To analyse this in some greater detail, we draw choropleth maps of labour productivity and FDI in China for the two sample periods 1992 and 2006. In the maps, Chinese provinces are divided into three groups based on the amount of FDI flows they have received. It is obvious from Figure 2 to Figure 4 that in China the regional distribution of labour productivity, FDI and trade exhibit a clear positive spatial dependence both in 1992 and in 2006. In other words, we can clearly observe from the maps that regions with high or low values in terms of labour productivity as well as FDI and trade intensity are strongly clustered.

<<< Figure 2 to 4 about here >>>

This picture is also confirmed, if we run spatial diagnostic tests. In the applied literature, the most widely used test is Moran's *I*, which can be easily extended to the case of panel data (see Lopez et al., 2011).[9] Table 2 displays the results of the so-called space-time Moran's *I (STMI)* for the variables in the dataset. For all variables, the null hypothesis of spatial independence among observations is rejected at reasonable confidence levels. The test results thus give strong evidence for positive and significant spatial autocorrelation in the sample period from 1979 to 2006 and hint at the likely advantage of using a spatially extended modelling framework to correctly identify the linkages between labour productivity (growth) and the set of regressors. A graphical presentation for the case of regional labour productivity is given in Figure 5. Here, the slope coefficient of a bivariate regression approach including (standardized) labour productivity and its spatial lag is equal to the size of the *STMI* as calculated in Table 2.

<<< Table 2 about here >>>

<<< Figure 5 about here >>>

Given the fairly long time dimension of our dataset at hand, we finally aim to determine the time series properties of the underlying variables. Table 3 therefore reports the results of the Im-Pesaran-Shin (2003) and Pesaran (2007) panel unit roots tests.[10] The results show that for most variables the null hypothesis of a unit root is rejected after first differencing the variables.[11] Generally, we can conclude that we have a non-stationary system for estimation and thus the existence of a stable

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[9] In cross-section settings Moran's *I* for variable *y* is defined as $I_y = \frac{N}{S_0} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}^{(y)} z_i z_j}{\sum_{i=1}^{N} z_i^2}$, $\forall$ all $t=1,2,...,T$, where, for a given year t and spatial lag y: $i \neq j$, N is the number of regions, z_i, and z_i, are normalized vectors of observed values of the variable at locations i and j, w_{ij} is the element of spatially weighting matrix $W(N \times N)$ corresponding to the observation pair i and j and S_0 is a scaling constant (see Moran, 1948). Moran's *I* statistic can be interpreted as the statistic measure of covariance of observations in nearby provinces relative to the variance of the observations across regions. For panel data setting a simple extension is to define the space-time Moran's *I* (STMI) as $STMI_y = \Gamma_T \otimes I_y$, where Γ_T is an identity matrix of dimension *T*.

[10] The latter approach by Pesaran (2007) has the advantage that it is relatively robust with respect to cross-sectional dependence in the variable, even if the autoregressive parameter is high (see e.g. Baltagi et al., 2007, as well as de Silva et al., 2009, for extensive Monte Carlo simulation evidence).

[11] Only for trade openness we get statistical support for stationarity in levels, while the Im-Pesaran-Shin test does not reject the existence of a unit root even in the first differences of infrastructure equipment.

cointegration relationship is of vital importance for not running spurious regressions. We will test for cointegration among the variables throughout our estimation exercise, which will be reported in the next section.

<<< Table 3 about here >>>

4. Empirical Results

4.1. Full sample

The estimation results of the SpECM regression approach according to eq.(3) and eq.(4) show that most variables and their respective spatial lags turn out significant in the long- and short-run equation.[12] Capital intensity, trade openness, infrastructure equipment and the share of institutions of higher education have a statistically significant coefficient in the long-run equation. Also, most included spatial lags turn out to be statistically significant. In the short-run, only capital intensity, the human capital variables and their spatial lags, as well as the spatial lag of inward FDI activity show a non-zero correlation with labour productivity growth. Moreover, the included error correction terms appear to be statistically significant and show a negative coefficient sign indicating that global error correction is at work. This implies that long-run imbalances in a region's productivity growth caused by disequilibria in the own region and the neighbor regions are being corrected in each period (see also Marquez et al., 2010). The result is a first strong indication for the existence of long term interregional spatial externalities.

As shown by the adjusted R^2, our approach captures more than 90% of the variation in long-run productivity levels among Chinese provinces. With respect to the more volatile short-run dynamics, our structural approach still accounts for roughly one-fourth of the total variation in labour productivity growth. We do not get any evidence for remaining spatial correlation in the residuals of the regression equations as shown by the Z_{STMI} values for both types of spatial weighting matrices; moreover the residual based Kao (1999) cointegration test strongly favors the existence of a stable cointegration relationship among the variables. As our regression results also show, the obtained coefficients are quite robust regarding the chosen spatial weighting

[12] For regression details see Table A.1 in the appendix.

matrix (linear contiguity and inverse distances) - both in terms of statistical significance as well as coefficient size.[13]

Although the estimation results already give a first indication regarding the statistical significance of the included variables, one has to note that the regression coefficients of the explanatory variables cannot be directly interpreted as elasticities, measuring the impact of an explanatory variable x on y in terms of $\partial y / \partial x$. As LeSage and Pace (2009) point out, unlike the parameters from a linear regression model, in models containing spatial lags of the explanatory or dependent variables the interpretation becomes richer and more complicated given that spatial regression models expand the information set to include information from neighboring observations. In addition, as recently shown by LeSage and Pace (2010), properly calculated marginal effects for spatial regression models yield robust results irrespective of the chosen spatial weighting matrix.

The authors thus propose a categorization measuring the average direct, indirect and total effect for each regressor. Thereby, the impact of a change in regressor x for region i on the endogenous variable y in i is said to be the regressor's direct effect.[14] Additionally, a change in the regressor x can also have an indirect impact on y in i, which arises from spatial spillovers of changes in the observations for all neighbouring regions j. The average total impacts are obtained by summing up the direct and indirect effects and averaging them over all regions. Table 4 reports the corresponding direct, indirect and total effects for our regional labour productivity, both in the long- and short run.

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[13] The only notable difference is the regression coefficient for the spatial lag of infrastructure in the long-run equation. Here, both matrices may capture different effects: The distance based approach reports a positive coefficient, which is likely to capture the effect of large infrastructure investments, which are mainly undertaken in the coastal regions (including the capital Beijing). As Marquez et al. (2011) have recently shown for the case of Spain, large infrastructure investments (especially in capital regions) may have a strong impact even on peripherical region, which do not necessarily need to share a common border with the region, where the infrastructure project is installed. On the contrary, the binary distance matrix reports a statistically significant negative effect, which is likely to capture the competitiveness effect of infrastructure investment among neighbouring regions. That is, a region with high investments in infrastructure may be able to poach production factors from its geographical neighbourhood. This effect is better captured by a binary contiguity matrix, especially for large geographical systems such as China.

[14] Direct effects also include feedback influences that arise from the impacts passing through the neighbours and back to the observation itself.

<<< Table 4 about here >>>

It can be observed from Table 4 that most of the variables exhibit a statistically significant direct effect in the long-run equation. In line with the existing literature, the total effects indicate that human capital and infrastructure development are the key determinants of labour productivity in Chinese regions on the long run. The long-run equation results also give evidence for a significant and positive total impact of FDI and trade openness on productivity. Moreover, trade openness and inward FDI activity show to be the source of significant spatial spillover effects on the growth performance in neighboring regions. The same holds for human capital while -as expected- the share of state owned enterprises has a negative spatial spillover effect pointing at inefficiencies introduced by a large state sector.[15]

In the short-run, besides direct, indirect and total effects emanated from both human capital variables, also inward FDI exhibits positive spatial spillover effects and a statistically significant positive direct effect. These results hint at the important role played by foreign investors in driving the long-run productivity level in Chinese provinces as well as short-run growth. They are also in line with the findings of Jiang (2011) and Lin *et al.* (2009) that demonstrate positive productivity spillovers to Chinese economy arising from internationalization activity.

4.2. Robustness tests for sub-samples

China's integration into the world economy was a gradual and spatially uneven process. In order to capture different productivity patterns over time, we split our sample into two sub-periods, namely 1979-1991 and 1992-2006. We therefore estimate eq.(3) and eq.(4) separately for each sub-period. The first stage of China's integration to the world economy is, above all, characterized by special regimes and large disparities in opening up paces between regions. Table 5 shows the estimated direct, indirect and total effects for the period 1979-1991.

<<< Table 5 about here >>>

[15] The low economic performances of the state owned enterprises (SOEs) in China has been a big concern for the government. For a comprehensive analysis of the SOE reform in China, the interested reader could refer to Yifu *et al.* (2001).

The table shows that between 1979 and 1991 the long-run labour productivity in Chinese regions was mainly determined by inward FDI and infrastructure development. For FDI we find both a positive direct as well as indirect effects. Trade openness and human capital mainly exhibit a direct but no statistically significant total effect. In the short-run equation, again FDI and infrastructure are tested to be statistically significant and of positive sign, here also the schooling variable shows to have a strong positive indirect spatial effect on the neighbouring regions' growth performance, while spatial spillovers from a high share of state enterprises in the geographical neighbourhood are negative. The same holds for short-run effects of infrastructure equipment, which is found to be significantly negative. One likely explanation is that regions with large infrastructure projects are able to poach production capacities from neighbouring regions.

The second stage of China's integration to the world economy has been above all marked by a progressive shift from preferential to a nationwide opening-up strategy. Table 6 shows that for this period the determinants of short- and long-run productivity development to some extent differ from the first subsample. Here it can be observed that capital deepening and the availability of highly educated workforce are the main drivers of labour productivity. For this period, spatial spillovers are generally less present compared to the first subsample from 1979-1991.

<<< Table 6 about here >>>

5. Conclusion

In this study, we focus on a panel of Chinese provinces and investigate the influence of several key economic and policy related factors on labour productivity. We put a particular focus on analysing the impact of opening up the economy to international trade and capital flows on regional productivity (growth). Moreover, by introducing spatial effects to the model, we aim at drawing a clearer picture of regional productivity spillovers and agglomeration effects. Extending the early empirical literature on the latter subject, this study represents one of the first attempts to apply a combination of the tools from times-series analysis and spatial econometric techniques in panel data structure. By using a spatial extension to the commonly know cointegration and error correction modelling approach, we are able to identify the long- and short-run driving forces of provincial labour productivity in China for the period 1979-2006. Our empirical outcomes report that, consistent with economic theory, human capital, infrastructure development and capital intensity could be recognised as main determinants of labour productivity. In addition, FDI and trade openness also exert a positive impact on productivity performances of Chinese regions. Especially FDI activity is found to be a source of positive spatial spillovers, both in the long- as well as short-run perspective. Thereby, FDI effects were especially found to be of vital importance in the first phase of Chinese opening up between 1979 and 1991, thus forming the (welfare and technology) basis for productivity growth driven by national capital deepening in the later period 1992-2006.

Our empirical results also hint at the fact that the geographical environment has a strong influence on the level of labour productivity. That is to say, the more a region is surrounded by high-productive regions with a good infrastructure, a large stock of human capital and linkages to the world economy, the more its productivity is expected to be high. This finding has serious policy implications: Preferential policies that solely consist of opening up some selected regions are not optimal for China. In order to reap more benefits from foreign presence, coordinated industrial policies which reinforce regional complementarities are needed. In addition, the removal of restrictions to the free movement of production factors across regional borders appears to be crucial to improve productivity levels.

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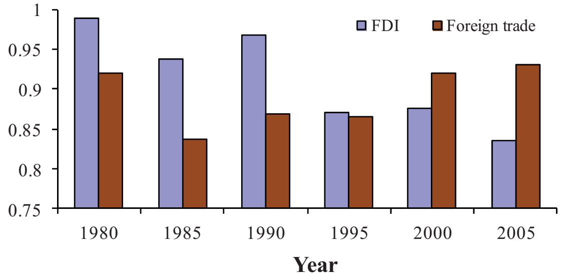
Table 1: Descriptive statistics (in logs)

Variable	*lprod*	*capital*	*fdi*	*trade*	*infra*	*high edu*	*basic edu*	*state*
Obs.	840	840	840	840	840	840	840	840
Mean	-1.660	-0.570	-2.511	-1.704	1.241	-1.737	-5.206	-1.742
Std. Dev.	0.936	1.485	2.251	5.536	0.784	0.568	0.905	0.542
Min.	-5.036	-13.816	-13.816	-13.816	-1.470	-3.130	-6.877	-3.130
Max.	0.711	2.155	1.104	5.582	3.180	3.160	-2.555	-0.545

Notes: All of the variables are explained in log linear form.

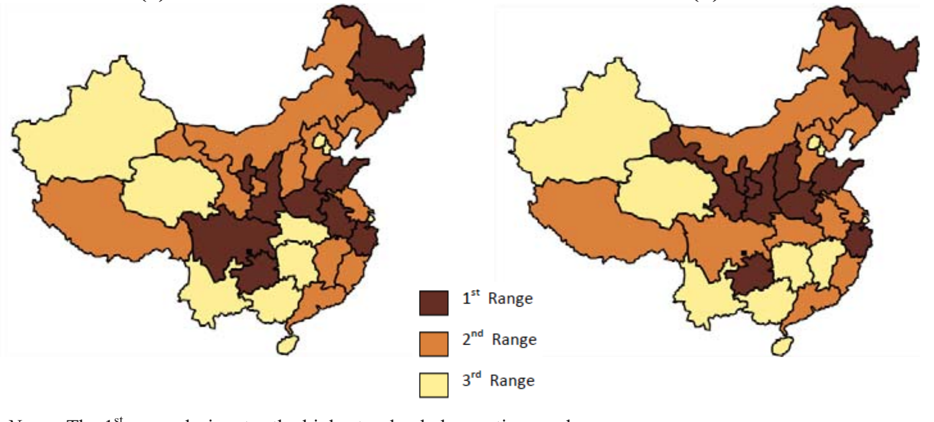
Figure 1: Share of inward FDI, foreign trade in coastal regions in China (1=100%)



Source: China Statistical Yearbook (2006); Authors' map.

Figure 2: Spatial dispersion of labour productivity in mainland China

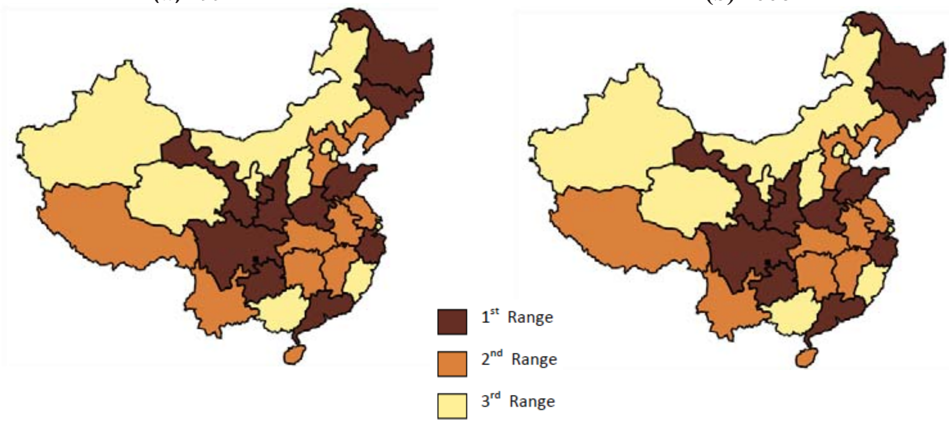
(a) 1992 **(b) 2006**



Notes: The 1st range designates the highest-valued observations and so on.

Figure 3: Regional distribution of FDI in mainland China

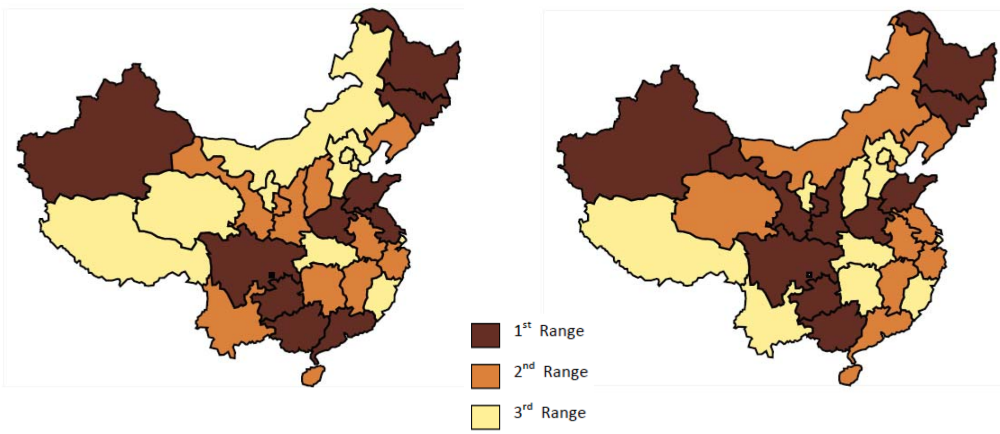
(a) 1992 **(b) 2006**



Notes: The 1^{st} range designates the highest-valued observations and so on.

Figure 4: Regional distribution of trade openness in mainland China

(a) 1992 **(b) 2006**



Notes: The 1^{st} range designates the highest-valued observations and so on.

Table 2: Space-Time Moran's I statistic for variables in dataset, 1979-2006.

	STMI	Z_{STMI}	*P-Value*
lprod	0.527	45.89	(0.00)
capital	0.299	26.72	(0.00)
fdi	0.204	17.89	(0.00)
trade	0.324	28.47	(0.00)
infra	0.625	54.36	(0.00)
high edu	0.405	35.19	(0.00)
basic edu	0.440	38.32	(0.00)
state	0.644	56.16	(0.00)

Notes: Results are based on the row-standardized binary contiguity matrix.

Figure 5: STMI for labour productivity, trade and FDI in China, 1979-2006

(a) Labour productivity

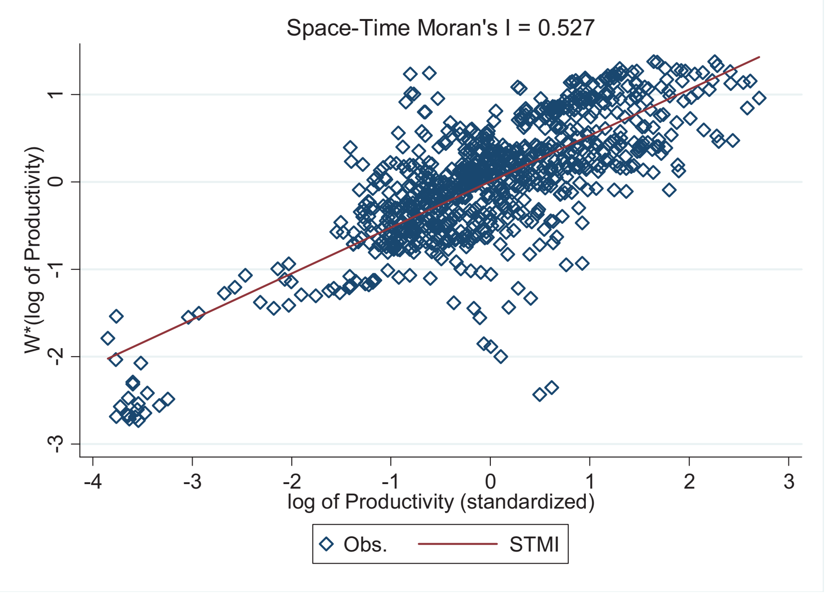


Table 3: Panel unit root tests

Variable	IPS W[t-bar] (P-Value)	CADF Z[t-bar] (P-Value)
	Levels	
lprod	17.80 (0.99)	1.07 (0.86)
capital	10.07 (0.99)	1.91 (0.97)
fdi	-1.98** (0.02)	-1.189 (0.11)
trade	-3.32*** (0.00)	-2.39*** (0.00)
infra	24.25 (0.99)	1.87 (0.96)
high edu	12.73 (0.99)	0.81 (0.79)
basic edul	4.80 (0.99)	0.01 (0.50)
state	17.46 (0.99)	1.43 (0.92)
	First Differences	
Δlprod	-12.58*** (0.00)	-8.37*** (0.00)
Δcapital	-13.14*** (0.00)	-7.06*** (0.00)
Δfdi	-20.34*** (0.00)	-18.37*** (0.00)
Δtrade	-17.17*** (0.00)	-11.52*** (0.00)
Δinfra	5.33 (0.99)	-3.33*** (0.00)
Δhigh edu	-7.36*** (0.00)	-8.29*** (0.00)
Δbasic edu	-4.94*** (0.00)	-2.01** (0.02)
Δstate	-4.76*** (0.00)	-3.10** (0.00)

Notes: ***, **, * denote significance at the 1, 5 and 10% level, *P*-values in brackets. For IPS, the optimal lag length is chosen according to the AIC. H_0 for both panel unit root test states that all series contain a unit root, $N=30, T=28$.

Table 4: Direct, indirect and total short-run effects on *lprod* (1979-2006)

	direct	indirect	total
		Long-run	
capital	0.0214***	-0.0064	0.0149
fdi	0.0040***	0.0218***	0.0259***
trade	-0.0063**	0.0501***	0.0438**
infra	0.1921***	0.0137	0.2059*
high edu	0.4985***	-0.0475	0.4509***
basic edu	-0.0118	0.2608**	0.2489*
state	-0.0190	-0.2838***	-0.3029
		Short-run	
Δcapital	0.0187***	0.0077	0.0265*
Δfdi	0.0006	0.0058**	0.0064**
Δtrade	-0.0004	0.0064	0.0060
Δinfra	0.0113	0.0025	0.0139
Δhigh edu	0.2619***	-0.0942**	0.1676***
Δbasic edu	0.1113***	0.1312***	0.2425***
Δstate	0.0165	0.0206	0.0372

Notes: ***, **, * denote significance at the 1, 5 and 10%-level based on partial derivatives and parameter simulations as described in LeSage and Pace (2009). Computations based on binary contiguity based spatial weighting matrix.

Table 5: Direct, indirect and total short-run effects on *lprod* (1979-1991)

	direct	indirect	total
	Long-run		
capital	0.0032	-0.0294*	-0.0261
fdi	0.0030**	0.0270***	0.0300***
trade	-0.0082***	0.0241*	0.0159
infra	0.5240***	0.2485	0.7725**
high edu	0.3111***	-0.1868	0.1242
basic edu	-0.2535***	0.3936**	0.1401
state	-0.0361	-0.2228	-0.2590
	Short-run		
Δcapital	0.0138***	-0.0216*	-0.0078
Δfdi	0.0015	0.0043*	0.0058**
Δtrade	0.0044	0.0051	0.0095
Δinfra	-0.1048	-1.6116***	-1.7164***
Δhigh edu	0.1110***	-0.1446**	-0.0336
Δbasic edu	0.1413*	0.8526***	0.9939***
Δstate	-0.0665	-0.8449**	-0.9114**

Notes: ***, **, * denote significance at the 1, 5 and 10%-level based on partial derivatives and parameter simulations as described in LeSage and Pace (2009). Computations based on binary contiguity based spatial weighting matrix.

Table 6: Direct, indirect and total short-run effects on *lprod* (1992-2006)

	direct	indirect	total
		Long-run	
capital	0.2386***	0.2741***	0.5127***
fdi	-0.0105	-0.0068	-0.0173
trade	0.0833***	-0.0686	0.0147
infra	0.0449*	-0.2019*	-0.1570*
high edu	0.2322***	-0.0424	0.1898**
basic edu	0.0451	-0.1986	-0.1535
state	0.0154	-0.0980	-0.0826
		Short-run	
Δcapital	0.2416***	0.0398	0.2815***
Δfdi	-0.0033	-0.0087	-0.0120
Δtrade	-0.0143	0.0344	0.0201
Δinfra	-0.0159	0.0116	-0.0042
Δhigh edu	0.1864***	-0.0448	0.1416***
Δbasic edu	0.1113***	0.0226	0.1340**
Δstate	0.0130	0.0051	0.0181

Notes: ***, **, * denote significance at the 1, 5 and 10%-level based on partial derivatives and parameter simulations as described in LeSage and Pace (2009). Computations based on binary contiguity based spatial weighting matrix.

Appendix

Box A.1: Transmission channels to local technology adaption through MNCs

- ***Imitation-demonstration and contagion effects:*** Foreign invested firms generally enjoy higher technological intensity and are expected to bring in new products and technologies to the recipient economy. In addition, geographic proximity to foreign firms is likely to stimulate close observation of technologies and imitation of high-technology products (Blomström and Wang 1992).
- ***Competition:*** The presence of foreign owned enterprises generally exerts a competitive pressure which might push local firms to improve their technological efficiency (Kokko 1996). In addition, in host countries where competition is fierce, MNCs could be more inclined to transfer their most advanced technologies to their subsidiary companies.
- ***Labour turnover:*** In developing countries, MNCs carry most of the R&D and training activities. Knowledge created in MNCs is likely to diffuse to local economy in various ways, for instance through labour turnover and when skilled workers trained in the MNCs establish businesses of their own (Blomström and Sjöholm 1999).
- ***Backward and forward linkages:*** In the presence of quality linkages between foreign firms and their local suppliers or customers, spillovers can take place in the form of labour training and technological know-how transfer.
- **Trade:** The expansion of foreign trade could increase technical efficiency in various ways. The expansion of exports is expected to enlarge market size and generate scale economies. The export activity of MNCs could stimulate the integration of local firms into international markets. The export-oriented FDI firms could reduce information costs in foreign markets and ease the establishment of adequate transport and communication infrastructure facilities. Furthermore, foreign currency brought by exports could finance the import of sophisticated equipment and machinery and foster technological upgrade.

Table A.1: SpECM regression results for Chinese provinces 1979-2006

Dep. Var: *Δ lprod*	**Binary contiguity**		**Distance based contiguity**	
	Long-run			
capital	0.021***	(0.005)	0.018***	(0.004)
fdi	0.002	(0.001)	-0.007***	(0.002)
trade	-0.009***	(0.003)	-0.008***	(0.003)
infra	0.188***	(0.029)	0.062**	(0.030)
high edu	0.502***	(0.018)	0.383***	(0.034)
basic edu	-0.031	(0.028)	0.035	(0.030)
state	0.001	(0.294)	-0.001	(0.003)
W *x capital*	-0.016*	(0.009)	0.023	(0.032)
W *x fdi*	0.007**	(0.003)	0.021***	(0.004)
W *x trade*	0.027***	(0.007)	-0.010	(0.011)
W *x infra*	-0.105**	(0.051)	0.123**	(0.059)
W *x high edu*	-0.322***	(0.033)	-0.336***	(0.051)
W *x basic edu*	0.131***	(0.055)	0.033	(0.080)
W *x state*	-0.122***	(0.041)	-0.188***	(0.066)
W *x lprod*	0.599***	(0.034)	0.636***	(0.031)
	Short-run			
$u_{i,t-1}$	-0.047***	(0.016)	-0.049***	(0.016)
Δcapital	0.018***	(0.004)	0.018***	(0.004)
Δfdi	0.001	(0.002)	0.001	(0.001)
Δtrade	-0.001	(0.005)	0.001	(0.006)
Δinfra	0.011	(0.018)	-0.002	(0.016)
Δhigh edu	0.263***	(0.020)	0.275***	(0.020)
Δbasic edu	0.109***	(0.024)	0.112***	(0.024)
Δstate	0.015	(0.010)	0.015	(0.011)
W *x* $u_{i,t-1}$	-0.029	(0.038)	-0.172***	(0.072)
W *x Δcapital*	0.005	(0.012)	0.003	(0.018)
W *x Δfdi*	0.005**	(0.002)	0.004	(0.004)
W *x Δtrade*	0.006	(0.007)	0.016	(0.016)
W *x Δinfra*	0.001	(0.032)	0.091	(0.065)
W *x Δhigh edu*	-0.108**	(0.035)	-0.087	(0.055)
W *x Δbasic edu*	0.117**	(0.050)	0.141**	(0.065)
W *x Δstate*	0.017	(0.021)	0.056	(0.036)
W *x Δlprod*	0.071	(0.047)	0.055	(0.070)
Obs.	810		810	
R^2 *adj. (long-run)*	0.931		0.945	
R^2*adj. (short-run)*	0.263		0.266	
Z_{STMI} *residuals (P-value)*	0.317	(0.376)	0.609	(0.271)
Kao (1999) Cointegration	-9.61***	(0.00)	-9.61***	(0.00)

Notes: ***, **, * denote significance at the 1, 5 and 10% level. Standard errors are in brackets. Z_{STMI} is the *z*-statistic of the spatio-temporal version of Moran's *I* (STMI). Kao (1999) cointegration test using automatic lag selection by SIC with a maximum lag length of 5 periods.