University of Groningen

Revisiting cross-province energy intensity convergence in China

Jiang, Lei; Folmer, Henk; Ji, Minhe; Zhou, P.

Published in:
Energy Policy

DOI:
[10.1016/j.enpol.2018.06.043](https://doi.org/10.1016/j.enpol.2018.06.043)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2018

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Jiang, L., Folmer, H., Ji, M., & Zhou, P. (2018). Revisiting cross-province energy intensity convergence in China: A spatial panel analysis. *Energy Policy*, 121, 252-263. <https://doi.org/10.1016/j.enpol.2018.06.043>

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

Revisiting cross-province energy intensity convergence in China: A spatial panel analysis

Lei Jiang^{a,b}, Henk Folmer^c, Minhe Ji^d, P. Zhou^{e,*}

^a School of Economics & Management, Nanchang University, Nanchang 330031, China

^b School of Economics, Zhejiang University of Finance & Economics, Hangzhou 310018, China

^c Department of Economic Geography, Faculty of Spatial Sciences, University of Groningen, Landleven 1, 9747 AD Groningen, The Netherlands

^d School of Geographical Science, East China Normal University, 200241 Shanghai, China

^e School of Economics and Management, China University of Petroleum, No. 66 Changjiang West Road, Qingdao, China

ARTICLE INFO

Keywords:

Energy intensity
Convergence
Spatial spillover effects
Spatial econometric model
China

ABSTRACT

Understanding the convergence of energy intensity helps in assessing whether policies targeted at reducing energy intensity are effective and should thus be continued or reinforced. This paper analyzes the convergence of cross-province energy intensity in China based on panel data of 29 provinces for the period 2003–2015 by means of sigma convergence, kernel density analysis, and unconditional and conditional beta convergence. The empirical results show that the omission of spatial spillovers underestimates conditional beta convergence. We thus argue that the implementation of effective policy for reducing energy intensity depends not only on the driving forces in the own province but also on the spatial spillover effects in neighboring provinces, particularly technology transfer, knowledge spillovers, and the input-output relationship. From the analysis, it follows that adopting low-energy capital, attracting more FDI inflows and developing indigenous innovation capabilities are major policy handles.

1. Introduction

As the largest energy consumer and largest carbon dioxide emitter in the world, China's energy consumption has risen five-fold since the country's economic reform and opening up in 1978. In 2012, for the first time, China accounted for more than half of global coal consumption (BP, 2013). Due to its demand for energy, China is currently facing two major challenges: energy scarcity and environmental degradation (Jiang and Lin, 2012; Yao and Chang, 2014).

Energy efficiency improvement has been widely regarded as a cost-effective way to address both energy scarcity and environmental degradation (Andrews-Speed, 2009). Previous studies have been devoted to developing different indicators and models for tracking the economy-wide energy efficiency performance in China and elsewhere (Zhou and Ang, 2008; Zhou et al., 2012; Filippini and Zhang, 2016). Of the alternative energy efficiency indicators, the energy-GDP ratio has been widely used for analyzing and supporting policy analysis due to its ability to directly measure the link between energy consumption and economic activity, as well as its ease of interpretation (Metcalfe, 2008; Le Pen and Sévi, 2010; Stern and Jotzo, 2010; Liddle, 2010).

The Chinese central government has been aware of the need to reduce energy intensity for more than a decade (Herrerias et al., 2013). In

its 11th Five-Year Plan (2006–2010), it set an imperative target of reducing the overall energy intensity by 20% relative to the benchmark of 2005. Since there exist clear regional differences in energy resource endowments, economic growth patterns, and levels of technological development, the regional targets for reducing energy intensity vary across different provinces. As a result, in the 11th Five-Year Plan, more stringent targets were set for the eastern provinces than for the western provinces, with the central provinces taking an intermediate position. By the end of 2010, China had successfully reduced its aggregate energy intensity by 19.1%. In the 12th Five-Year Plan (2011–2015), the country-level energy intensity target was set at a reduction of 16% with reference to the year 2010. At the province level, as shown in Fig. 1, different energy intensity reduction targets have been assigned. Despite the efforts made by different provinces to reduce energy intensity, there still exist substantial gaps among them.

Understanding the provincial energy intensity gaps can help policy makers in designing and implementing effective policies to respond to the ever-growing environmental degradation in China. In this respect, two possible policy handles arise. One option is to focus on provinces that have already substantially reduced their energy intensity. However, this strategy is relatively expensive because it becomes increasingly difficult to further reduce their energy intensity because the

* Corresponding author.

E-mail addresses: lei.jiang@zufe.edu.cn (L. Jiang), pzhou@upc.edu.cn (P. Zhou).

Fig. 1. Regional energy intensity reduction targets (%) in the 12th Five-Year Plan. (Data source: http://www.gov.cn/gongbao/content/2011/content_1947196.htm)

low-hanging fruit has already been harvested. The other option is to focus on the “laggards” in an attempt to accelerate their energy intensity reduction, possibly by making use of the experiences of the “pioneers”. Either way, for sustainable economic development, China’s policy makers should better understand how provincial energy intensity changes over time (Burnett, 2016).

Convergence is a concept that stems from the economic growth literature, particularly the income growth literature (Barro, 1991). In energy intensity studies, the convergence concept has also been used, mostly at the country level. For instance, Mulder and De Groot (2007) showed that technological progress, knowledge spillover, technology diffusion, and sectoral shifts are important sources of energy intensity convergence. Miketa and Mulder (2005) analyzed energy productivity convergence (the reciprocal of energy intensity) in ten manufacturing sectors across 56 developed and developing countries for the period 1971–1995. Markandya et al. (2006) showed the convergence of energy intensity in a sample of European countries towards the European Union average. Mulder and De Groot (2007) investigated the convergence of cross-country energy productivity at the sectoral level using panel data of 14 OECD countries for the period 1970–1997. Herrerias (2012) investigated the convergence of energy intensity for 83 countries over the period 1971–2008 by means of the distribution dynamics approach. Kiran (2013) used a fractional cointegration model to investigate the energy intensity convergence of 21 OECD countries.

Similar to international convergence studies, there are several studies of energy intensity convergences at the regional level. A recent example is Burnett and Madariaga (2016), who found evidence of convergence in state-level energy intensity in the US. To the best of our knowledge, there are only few studies dealing with this issue in China. An example is Yu (2012), who applied spatial econometric models to test provincial energy intensity convergence. He found absolute beta convergence of provincial energy intensity and conditional beta convergence when taking into account spatial effects. Herrerias and Liu (2013), who found evidence of electricity intensity convergence across Chinese provinces based on monthly data for the period 2003–2009 by means of unit root tests. Pan et al. (2015) applied data envelopment analysis (DEA) and spatial Markov chain analysis to test the club convergence of regional energy efficiency. More recently, Zhang and Broadstock (2016) showed club convergence in cross-province energy

intensity. The study by Zhang et al. (2017) investigated the convergence of provincial energy efficiency by using DEA, considering spatial effects.

A crucial aspect of convergence analysis based on a sample of spatial units, as in the case of the present study, is spatial spillover, i.e., that the sample elements are not independent but interact with and influence each other. Although Yu (2012) took into account spatial effects, one shortcoming of his study in examining energy intensity convergence is that he ignored potential exogenous spatial effects. Technically speaking, a major vehicle of energy intensity convergence is technology diffusion across provinces. Explicit inclusion of the technology spillover vehicles in a convergence model is necessary not only from a substantive point of view but also from an econometric point of view. The omission of potential spatial spillovers may lead to omitted variable bias, i.e., to under- or overestimation of the determinants of convergence. Thus, it is necessary to include spillover effects in a convergence model to reduce potential model specification errors (Folmer and Oud, 2008). Otherwise, it may lead to biased conclusion, and even undermine scientific results.

The purpose of this paper is to model the convergence of energy intensity in China by considering both the own determinants of convergence and their spatial spillovers. In addition to spillovers in the systematic model components, we also test and control for spatially correlated disturbances (see Section 2.1). The remainder of this paper is organized as follows. Section 2 introduces the convergence models as well as the data used in this paper. Section 3 presents the modeling results. Section 4 concludes; it also includes some policy recommendations.

2. Methods and data

There are different convergence concepts and models in the literature, as summarized by Petterson et al. (2014). In this paper, we use the following three common concepts: σ convergence, kernel density analysis and β convergence.¹ σ convergence is defined as the decline in

¹ Because of the small sample size, we do not analyze stochastic convergence, which requires panel unit root tests (Le Pen and Sévi, 2010).

dispersion across a group of units. It is measured as the development of the standard deviation (SD) over time (Barro and Sala-i-Martin, 1991; Mulder and De Groot, 2007). Meanwhile, we also consider kernel density to analyze σ convergence. β convergence is described below.

2.1. β convergence

β convergence focuses on the relationship between the initial level of a variable (i.e., energy intensity) and its growth rate. A significant, negative β indicates that provinces with high energy intensity catch up with provinces with lower energy intensity. By including the key determinants of energy intensity into the relationship, β convergence analysis provides insight not only into the differences in energy intensity among provinces but also into the driving forces behind convergence patterns. Thus, it provides information for policy-making (Miketa and Mulder, 2005).

Energy intensity may converge to a common steady state for all provinces or to different steady states for different subsets of provinces. To that end, the concept of β convergence is divided into two types: unconditional and conditional convergence. The former analyzes whether all provinces converge to a common steady state, whereas the latter refers to different subsets converging to different steady states that are conditional upon province-specific characteristics.

Globally, three types of models may be used to capture spatial spillover effects: the spatial lag model, the spatial Durbin model and the spatial Durbin error model (SDEM) (LeSage and Pace, 2009; Elhorst, 2014).² Typical for the spatial lag model, is spillover for the dependent variable. This model was applied by Huang and Meng (2013) to analyze the convergence of per capita carbon dioxide emissions in urban China. A spatial Durbin model allows for spatial spillover for the dependent variable and for the exogenous variables. Zhao et al. (2015) applied a dynamic spatial Durbin panel data model to test for carbon dioxide emissions intensities at the province level among 30 Chinese provinces. In their model specification, the dependent variable is assumed to be affected by (i) own exogenous variables, (ii) exogenous variables in neighboring provinces (spatially lagged exogenous variables) such as interregional input-output variables, and (iii) the spatial spillover effects of the dependent variable. Note that, in this case, the spatial transfer is direct rather than indirect. That is, emissions generated in the own province are deposited by the same (direct) mechanism as that in neighboring provinces, i.e., atmospheric circulation.

Our study differs from Huang and Meng (2013) and Zhao et al. (2015) in that we do not hypothesize a spatially lagged endogenous variable. The reason is that the spatial spillover in the case of energy intensity convergence occurs via indirect mechanisms such as input-output linkages rather via a direct mechanism. Even in the case of knowledge spillovers, there is an intermediate mechanism rather than a direct mechanism, such as interregional transfers of physical or human capital. Since we allow for spatially lagged exogenous variables and spatially correlated residuals, we opt for the spatial Durbin error model.

2.1.1. Unconditional convergence

Unconditional convergence relates to converging to a common steady state. In terms of the SDEM, the unconditional energy intensity convergence model is:

$$EIG_{it} = \alpha + \beta \text{Ln}EI_{it-1} + \varepsilon_{it} \quad (1a)$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^N w_{ij} \varepsilon_{ijt} + \nu_{it} \quad (1b)$$

where EIG_{it} denotes the growth in the energy intensity of province i at time t in logs, $\text{Ln}EI_{it-1}$ the natural logarithm of lagged energy intensity EI

and α the constant term. The spatially correlated error term ε depends on the error term of the neighboring provinces and an idiosyncratic component ν .

w_{ij} in (1b) is an element of the $N \times N$ spatial weights matrix W that captures the spatial structure of Chinese provinces. We apply a binary first-order rook contiguity spatial weights matrix whose elements equal 1 if two provinces share a common border and 0 otherwise. Note that Kelejian and Piras (2014) argued that the rook spatial weights matrix can be taken to be exogenous rather than endogenous. λ is the spatial autocorrelation coefficient. The sign of β indicates β convergence. If β is negative and significant, then there is significant β convergence.

Note that Islam (1995), Mulder and De Groot (2007), and Zhao et al. (2015) proposed that the parameter of convergence, β , is taken as an exponential decay function. We follow the specification by Mulder and De Groot (2007) to estimate the implied rate of energy intensity convergence, that is, $\beta = -(1 - e^{-\gamma\tau})$. The parameter γ , defined as $\gamma = -\ln(\hat{\beta} + 1)/\tau$, is called the implied rate of convergence, and τ is the time interval. We follow the recommendation by Islam (1995), Mulder and De Groot (2007), and Zhao et al. (2015) in that we report both β and γ below. We also follow Islam's (1995) suggestion to apply various estimation intervals to test the stability of the coefficients of convergence. In addition to a one-year interval, we apply two-year and three-year intervals. See also Burnett and Madariaga (2016). Note that the above observations also apply to conditional convergence, which we discuss next.

2.1.2. Conditional convergence

As mentioned above, conditional convergence allows different subsets of provinces to converge to different levels, depending on province-specific conditions. One way of modeling conditional convergence is by controlling for individual specific fixed effects and time period fixed effects, i.e., by applying the following fixed effects spatial Durbin error model:

$$EIG_{it} = \alpha + \beta \text{Ln}EI_{it-1} + \mu_i + \eta_t + \varepsilon_{it} \quad (2a)$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^N w_{ij} \varepsilon_{ijt} + \nu_{it} \quad (2b)$$

where μ_i and η_t represent the spatial fixed effects and the time period fixed effects, respectively.³ All other variables are the same as in Eq. (1).

A more informative and possibly more adequate model is the general spatial Durbin error model, which contains controls and their spatial spillovers:

$$EIG_{it} = \alpha + \beta \text{Ln}EI_{it-1} + \mathbf{x}_{it} \theta + \sum_{j=1}^N w_{ij} \mathbf{x}_{ijt} \delta + \mu_i + \eta_t + \varepsilon_{it} \quad (3a)$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^N w_{ij} \varepsilon_{ijt} + \nu_{it} \quad (3b)$$

where $\mathbf{x}_{it}$ is a $1 \times K$ row vector of exogenous variables (in this case, in logs) and θ a $K \times 1$ column vector of coefficients. In a similar vein, the $1 \times K$ row vector $\mathbf{x}_{ijt}$ with $K \times 1$ column vector of coefficients δ contains the controls in neighboring provinces that affect growth EIG_{it} . All other variables are the same as in Eqs. (1) and (2).

Note that Eq. (3a) explicitly models the spatial spillover effects of the controls, i.e., that energy intensity convergence in a given province is influenced by the exogenous variables in neighboring provinces and vice versa. It should be observed that this modeling approach indicates whether the spatial spillover effects can accelerate convergence. In

² The three models are sub-models of the general nesting spatial model, whereas various sub-models can be obtained from the above three general models (see Elhorst, 2014).

³ The random effects model is implausible because of the substantial structural differences among Chinese provinces, which make it highly unlikely that the observations are randomly drawn from a large population (Islam, 2003). Nevertheless, we test the fixed effects model versus the random effects model.

Table 1

The variables, their definitions, measurements and expected signs of their impacts on energy intensity growth.

Data sources: China Energy Statistical Yearbook (2004–2016), China Statistical Yearbook (2004–2016), China Industry Economy Statistical Yearbook (2004–2016) and China Economic Database (CEIC)

Variable	Definition	Unit	Expected sign
<i>EIG</i>	Energy intensity growth: The natural logarithm of the ratio of <i>EI</i> at <i>t</i> and <i>t</i> – 1	Ton/10,000 Yuan	
<i>EI</i>	Energy intensity: The ratio of energy consumption to <i>GDP</i>	Ton/10,000 Yuan	±
<i>GPPc</i>	<i>GPP</i> Per capita	10,000 Yuan/capita	±
<i>Secondsec</i>	The share of the secondary sector in <i>GPP</i>	%	+
<i>Invest</i>	The share of investment to <i>GPP</i>	%	+
<i>Caplaborratio</i>	The ratio of capital to labor	10,000 Yuan/full time labor	–
<i>FDI</i>	The ratio of FDI to <i>GPP</i>	%	–
<i>Enresc</i>	Energy reserves per capita	Ton/capita	+

Note: A negative sign indicates convergence.

particular, the significance of the spatially lagged variables and an increase in the adjusted R^2 and log-likelihood values are indications that spatial spillovers accelerate convergence (see Section 3).

2.1.3. Explanatory variables of conditional convergence

Based on the literature review, we now discuss the controls in Eq. (3a), which include gross provincial product per capita (*GPPc*), the share of the secondary sector (*Secondsec*), investment in real estate and infrastructure (*Invest*), the capital-labor ratio (*Caplaborratio*), foreign direct investment (*FDI*), and energy reserves (*Enresc*). The variables and their definitions, measurements and expected signs are presented in Table 1.

2.1.3.1. *GPPc*. The impact of this variable on energy intensity development is ambiguous. On the one hand, more income leads to more consumption and investment, which, at an early stage of development, may increase energy intensity (the upward sloping part of the environmental Kuznets curve (Cole and Rayner, 2000)). On the other hand, as income rises, citizens become environmentally aware and demand protection via environmental regulation (the downward sloping part of the environmental Kuznets curve (Suri and Chapman, 1998; Song and Zheng, 2012)). In addition, rising income tends to push the economic structure towards lower energy-intensive industries (Suri and Chapman, 1998) and induces environmentally friendly research and development and the application of more advanced, energy-efficient technology (Komen et al., 1997). Hence, under these conditions, *GPPc* has a negative impact on energy intensity growth.

2.1.3.2. *Secondsec*. The secondary sector is the largest energy consumer in China. For example, it accounted for 65.17% of total energy consumption in 2015 but merely produced 40.9% of China's GDP. Although the share of the secondary sector has gradually declined in recent years, it still accounts for the majority of the economy. The larger the share of the secondary sector is, the more energy intensive a province is, ceteris paribus. Hence, we expect *Secondsec* to have a positive impact on energy intensity growth.

2.1.3.3. *FDI*. Foreign direct investment is a major vehicle for developing countries to acquire advanced technologies and knowledge from developed countries. Thus, it is expected to have a negative impact on energy intensity growth (Mulder and De Groot, 2007; Hübler and Keller, 2010). Zheng et al. (2011) and Herrerias et al. (2013) showed that the large quantities of FDI flowing into China had reduced its overall energy intensity.

Note that, according to the pollution haven hypothesis, energy-intensive industries tend to migrate to poor developing countries since they usually have relatively low environmental standards compared with advanced industrialized countries. Indeed, at the beginning of China's policy of economic reform and opening up implemented in 1978, a massive amount of foreign capital flew into China's heavy industries (Jiang et al., 2017), inter alia, because of its lax environmental standards. However, since the turn of the century (including the research period), Chinese environmental standards for FDI have rapidly become stricter, even for energy-intensive industrial sectors. For example, the processing of petroleum and nuclear fuel and the manufacturing of raw chemical materials have seen an increase in environmental protection (see, e.g., Herrerias and Orts, 2010; Elliott et al., 2013; Jiang et al., 2017). Hence, the pollution haven hypothesis holds less and less for China. We hypothesize that *FDI* has a negative impact on the growth in energy intensity.

2.1.3.4. *Invest*. In recent years, the Chinese central government has stimulated the country's economy by means of large-scale investments in real estate and infrastructure. Accordingly, substantial amounts of energy-intensive products, such as cement and steel, have been consumed. We expect *Invest* to have a positive impact on energy intensity growth.

2.1.3.5. *Caplaborratio*. The capital-labor ratio is used as a proxy for the vintage of capital (Metcalfe, 2008). A low *Caplaborratio* indicates old-fashioned technology with high energy intensity. We hypothesize that *Caplaborratio* has a negative effect on the growth in energy intensity.

2.1.3.6. *Enresc*. Energy intensity is closely related to the energy resource endowment (Jiang et al., 2014). In particular, energy-rich provinces have developed energy-intensive industries over the years because of their easy access to energy resources. Hence, we hypothesize that *Enresc* has a positive effect on the growth in energy intensity.

2.1.3.7. Spatial spillover effects (*W*). As noted above, spatial spillover effects play an important role in affecting the convergence of cross-province energy intensity. An increase in per capita income in one province may stimulate income and energy consumption in neighboring provinces and thus increase energy intensity through the input-output linkage, labor force migration, and multi-regional companies. On the other hand, such an increase may dampen energy intensity since rising income may lead to demand for environmental quality and environmental protection. *Secondsec* in one province may also have an impact on the energy intensity in neighboring provinces if these sectors stimulate each other. As described above, the cross-province convergence of energy intensity is, inter alia, affected by knowledge spillover. This effect also applies to *FDI*. It may work in three ways, viz. via a demonstration effect, labor turnover and vertical linkage, i.e., the links between foreign firms in the own province and local suppliers in neighboring provinces (Cheung and Lin, 2004). New technologies and knowledge may be embedded in advanced capital, proxied by *Caplaborratio*. There will be a dampening effect on energy intensity when advanced capital flows and labor forces migrate from advanced provinces into lagging provinces. A positive spatial spillover effect of *Invest* in real estate and infrastructure results if this kind of investment in one province boosts similar investments in neighboring provinces. *Enresc* may have a positive spatial spillover effect when an energy-short province imports energy or energy resources from energy-rich neighboring provinces. Spatial lags are denoted by $W \times \text{variable name}$; they are measured in the same units as the own variables and are expected to have the same signs.

2.2. Data sources

Data for energy consumption are obtained from the China Energy

Table 2
Descriptive statistics.

Variable	Mean	SD	Min	Max
EIG	− 0.0417	0.0483	− 0.2581	0.1889
EI	1.5531	0.8253	0.4332	4.516
GPPc	2.2869	1.5292	0.3686	7.9730
Secondsec	47.8655	6.8516	21.2999	59.0450
Invest	58.0757	18.6288	25.3581	124.2257
Caplaborratio	9.8376	7.1060	1.0018	39.0991
FDI	2.5838	2.0666	0.0683	10.5118
Enresc	248.5059	514.1271	0.1557	2398.7430

Note: For definitions and sources, see Table 1.

Statistical Yearbook (2004–2016). Data for GDP, the share of the secondary sector, investment, capital, labor and energy reserves are available from the *China Statistical Yearbook* (2004–2016) and the *China Industry Economy Statistical Yearbook* (2004–2016). Data for FDI are obtained from the *China Economic Database* (CEIC). For details, refer to Table 1. All economic variables are taken in 2003 constant prices.

3. Results and discussion

As a preliminary to the empirical analysis, we present the descriptive statistics (means, standard deviations (SD), min and max values) across space and time in Table 2.

In this section, we empirically analyze σ convergence and β convergence of provincial energy intensity. The results and discussions about σ convergence are presented in the Appendix A. Then, we next discuss the results of β convergence of cross-province energy intensity. We first consider unconditional convergence, followed by the two types of conditional convergence. The estimation results are presented in Table 3.

Before going into detail and as noted above, we follow Islam's (1995) observation that a one-year time interval may not be robust and that longer time intervals may be needed to test how long an effect may last. Accordingly, we choose 2-year and 3-year time intervals for comparison. The results showed that the 3-year model outperformed the 1-year and 2-year models in terms of the significance of the hypothesized impacts of the explanatory relationships. See Appendix B. Accordingly, we selected the 3-year interval model for further analysis and discussion.

The second column in Table 3 presents the unconditional convergence results, based on models (1a) and (1b) above. The coefficient β is negative and insignificant ($\beta = -0.0034$, $\gamma = 0.0011$). The insignificance is most likely because there are large differences across provinces in terms of, inter alia, the economic structure, energy resource endowments, and level of technological development. As shown by Liddle (2009), a prerequisite for convergence is that the units of analysis (in this case, provinces) have similar economic structures. In the case of different economic structures, they will tend to grow towards their own steady states. In other words, the estimated models (1a) and (1b) point towards conditional convergence analysis.

For robustness, apart from first-order rook contiguity spatial weights matrix we also take into account different spatial weights matrices, for example, economic distance and geographic distance spatial weights matrices to empirically test their spatial effects in the convergence models. Economic distance spatial weights matrix is described below (Lin et al., 2005).

$$W_{ij} = \begin{cases} \frac{1}{|\bar{Y}_i - \bar{Y}_j|}, & i \neq j \\ 0, & i = j \end{cases} \quad (4)$$

$$\bar{Y}_i = \frac{1}{t_1 - t_0 + 1} \sum_{t_0}^{t_1} Y_{it} \quad (5)$$

where Y is an economic variable. It usually takes per capita GDP. Then, Y_{it} represents income level of province i in year t . The elements of the matrix are the differences in average per capita GDP between two spatial units. One reason to take differences in per capita GDP between two provinces as economic distance spatial weights matrix is that the indicator GDP is a comprehensive informative indicator that can better reflect economic development levels of these provinces. The estimation results of convergence models with economic distance spatial weights matrix are presented in Table 4.

It can be found that the results in Table 4 are very similar to those in Table 3. Specifically, the estimated parameters of the convergence models in Table 4 are very close to those in Table 3, notably the implied rates of convergence. Besides, the spatial autocorrelation coefficients λ in all models in Table 4 are significant, indicating spatial dependence among the residuals. To sum up, the results of the two models have very little differences. However, the convergence models in Table 4 may suffer from the issue of endogeneity since the economic distance spatial weights matrix is taken to be endogenous. In this regard, the models in Table 3 outperform those models in Table 4.

In a similar vein, we next consider geographic distance spatial weights matrix to test spatial effects in the convergence models. In empirical studies, it may take inverse distance matrix. In other words, the elements of the matrix are the inverse distances between two provinces. Hence, the geographic distance spatial weights matrix is symmetric.

The estimation results of the convergence models with the geographic distance spatial weights matrix are presents in Table 5. We find that the estimated parameters of convergence models are also very similar to those in Tables 3 and 4. The largest differences are that the spatial autocorrelation coefficients of the convergence models except the model in column 2 in Table 5 are highly insignificant, indicating no significant spatial dependence among residuals. The possible reason is that the geographic distance spatial weights matrix may not suitable to this case. In other words, spatial dependence among the residuals cannot be described by the matrix. Alternatively, we may consider a radial geographic distance spatial weights matrix. Technically speaking, we may set a threshold distance or bandwidth. If the distance between two spatial units is smaller than the threshold, then there is a direct spatial influence, and no spatial influence otherwise. Since the threshold is a predetermined parameter and a strongest assumption, we ignore the matrix.

We will discuss the convergence results based on Table 3. The third column in Table 3 shows the estimated conditional convergence model with two-way fixed effects.⁴ We tested the null hypothesis that the spatial fixed effects are jointly insignificant by means of the likelihood ratio test. The Chi square value was 84.2128 with 29 degrees of freedom, $p < 0.01$, leading to the rejection of the hypothesis at the 1% significance level. In a similar vein, the hypothesis that the time-period fixed effects are jointly insignificant was rejected at the 1% significance level (Chi square value 132.4803 with 4 degrees of freedom, $p < 0.01$). Both outcomes justify controlling for spatial and time-period fixed effects. In addition, a Hausman test of a fixed effects model versus a random effects model was rejected.

The β coefficient of -0.2011 is significant and negative, indicating conditional convergence. The implied rate of convergence is 0.0748.

To shed light on the importance of spatial spillovers for accelerating convergence, we estimated the 3-year interval model without (Table 3, column 4) and with spatially lagged explanatory variables (Table 3, column 5). A comparison of these columns shows that the β coefficient substantially decreased from -0.1733 to -0.2318 and the implied rate increased from 0.0634 to 0.0879. Furthermore, several of the spillover effects were significant, and the adjusted R^2 increased from

⁴ Since the spatial and time-period fixed effects per se are not interesting, they are not presented here; they are available upon request from the first author.

Table 3
Three-year β convergence models of energy intensity.

Independent Variables	Unconditional model	Conditional model without controls	Conditional model with controls	Conditional initial model with spillovers	Conditional final model with spillovers
$\ln EI_{t-1} (\beta)$	– 0.0034 (– 0.5403)	– 0.2011*** (– 7.7257)	– 0.1733*** (– 6.8660)	– 0.2318*** (– 8.8694)	– 0.2332*** (– 8.9192)
Implied rate: γ	[0.0011]	[0.0748]	[0.0634]	[0.0879]	[0.0885]
$\ln GPPc$			– 0.1327*** (– 4.0621)	– 0.1390*** (– 4.4421)	– 0.1376*** (– 4.7112)
$\ln Secondsec$			0.0641** (2.1226)	0.0620** (2.3065)	0.0685* (2.6748)
$\ln FDI$			– 0.0083** (– 2.1833)	– 0.01014*** (– 2.6279)	– 0.0110*** (– 3.1142)
$\ln Enresc$			0.0025 (0.3815)	0.0030 (0.4953)	
$\ln Caplaborratio$			– 0.0054 (– 0.4109)	0.0046 (0.3804)	
$\ln Invest$			0.0307** (2.3149)	0.0333*** (2.6209)	0.0352*** (3.0966)
$W^* \ln GPPc$				– 0.1848** (– 2.4328)	– 0.2180*** (– 3.6470)
$W^* \ln Secondsec$				0.1825*** (2.8791)	0.1625*** (2.7089)
$W^* \ln FDI$				– 0.0312*** (– 3.5710)	– 0.0317*** (– 3.7594)
$W^* \ln Enresc$				0.0206 (1.5054)	0.0226* (1.6763)
$W^* \ln Caplaborratio$				– 0.0242 (– 0.7719)	
$W^* \ln Invest$				0.0713*** (2.5068)	0.0587** (2.4021)
Constant	– 0.0237*** (– 3.2998)	0.0517*** (5.2379)	0.9696*** (3.4278)	1.8105*** (2.5064)	2.1824*** (4.8715)
λ	0.6920*** (9.9468)	0.5959*** (7.1853)	0.3209*** (2.8722)	0.2651** (2.2824)	0.2950*** (2.5916)
Spatial fixed effects		84.2128***	110.7053***	116.1006***	114.3871***
Time fixed effects		132.4803***	38.9858***	35.9374***	35.3002***
Adjusted-R ²	0.0243	0.2466	0.4368	0.5760	0.5676
Log-likelihood	266.6687	327.8667	339.5517	355.2503	354.4139
Obs.	116	116	116	116	116

Notes: t statistics in parenthesis. Implied rates in brackets. *: $p < .10$, **: $p < .05$, ***: $p < .01$.

Definitions of the variables in Table 1.

W^* denotes the spatially lagged variable. $W_{ij} = 1$ if two provinces share a common border, 0 otherwise; $W_{ii} = 0$.

0.4368 (column 4) to 0.5760 (Initial model) and 0.5676 (Final model) in columns 5 and 6, respectively, indicating that the spatially lagged explanatory variables contributed to convergence. Similarly, the log-likelihood statistic also increased. We do not discuss the model without spatially lagged explanatory variables any further because of possible omitted variable bias.

The fifth column in Table 3 presents the estimated conditional model for 3-year intervals with all the “own” variables and their spatial lags. A significant and negative coefficient $\beta = -0.2318$ is found ($\gamma = 0.0879$). Since some variables in the Initial model (column 5) are insignificant, namely, $\ln Enresc$, $\ln Caplaborratio$, and $W^* \ln Caplaborratio$; we applied a stepwise backward elimination procedure to the Initial model. The outcome of the backward elimination procedure is the Final model (column 6), which we discuss next.

The coefficient of $\ln GPPc$ is significant and negative, indicating that rising income leads to a decline in the growth in energy intensity, which we assumed to be related to increased environmental awareness and investment in environment-related research and technological development. The coefficient of $W^* \ln GPPc$ is significant and negative, indicating that rising per capita income in neighboring provinces, via spatial spillovers, dampens the energy intensity growth in a province. The coefficient of $\ln Secondsec$ is also significant but positive, indicating

that the development of the secondary sector drives energy intensity growth up. The same is true for the coefficient of $W^* \ln Secondsec$, indicating the growth stimulating effects from neighboring provinces via inter-industrial input-output relationships. The coefficient of $\ln FDI$ is negative and significant, indicating that “own” FDI significantly reduces the energy intensity in a province. The same is true for $W^* \ln FDI$, indicating that there are significant growth dampening spatial spillover effects from neighboring provinces. The spatial spillover effects of large FDI inflows are responsible for boosting the level of advanced, low-energy technologies and leapfrogging (Herrerias and Orts, 2010) in a short period of time. This point is especially true in China, as over the last two decades it has been the largest recipient of FDI among all developing countries (Elliott et al., 2013). The coefficients of $\ln Caplaborratio$ is positive and insignificant, while the coefficient of $W^* \ln Caplaborratio$ is negative but also highly insignificant. Apparently, the volumes of more energy-saving vintages have not yet replaced the old-fashioned vintages with high energy intensity. The coefficients of $\ln Invest$ and $W^* \ln Invest$ are significant and positive, indicating that investment in real estate and infrastructure drives energy intensity in the own province and neighboring provinces up. The coefficient of $\ln Enresc$ is insignificant for the own province but significant and positive for spillovers. Apparently, neighboring provinces tend to make

Table 4Three-year β convergence models of energy intensity with economic distance spatial weights matrix.

Independent Variables	Unconditional model	Conditional model without controls	Conditional model with controls	Conditional initial model with spillovers	Conditional final model with spillovers
$\ln EI_{t-1} (\beta)$	– 0.0009 (– 0.1737)	– 0.1494*** (– 5.5713)	– 0.1581*** (– 6.5925)	– 0.2207*** (– 8.8941)	– 0.2237*** (– 8.8910)
Implied rate: γ	[0.0003]	[0.0539]	[0.0574]	[0.0831]	[0.0844]
$\ln GPPC$			– 0.1377*** (– 4.3293)	– 0.1274*** (– 4.3819)	– 0.1255*** (– 4.5813)
$\ln Secondsec$			0.0660** (2.2537)	0.0460* (1.7801)	0.0548** (2.1714)
$\ln FDI$			– 0.0104*** (– 2.9683)	– 0.0095*** (– 2.7032)	– 0.0103*** (– 3.2252)
$\ln Enresc$			0.0093 (1.5916)	0.0066 (1.1670)	
$\ln Caplaborratio$			– 0.0025 (– 0.2185)	0.0080 (0.7552)	
$\ln Invest$			0.0268** (2.0727)	0.0242** (2.0814)	0.0296*** (2.7925)
$W^* \ln GPPC$				– 0.1846*** (– 2.6464)	– 0.2177*** (– 4.0741)
$W^* \ln Secondsec$				0.1651*** (2.9753)	0.1495*** (2.7893)
$W^* \ln FDI$				– 0.0301*** (– 3.7683)	– 0.0299*** (– 3.8611)
$W^* \ln Enresc$				0.0169 (1.3851)	0.0226** (1.9546)
$W^* \ln Caplaborratio$				– 0.0206 (– 0.7358)	
$W^* \ln Invest$				0.0733*** (2.8359)	0.0634*** (2.8164)
Constant	– 0.0299*** (– 4.0429)	0.0318*** (3.0210)	0.9894*** (3.6258)	1.8358*** (2.6810)	2.1630*** (5.0046)
λ	0.7180*** (9.6358)	0.4536*** (3.8121)	0.5234*** (4.7967)	0.5730*** (5.6540)	0.5234*** (4.7966)
Spatial fixed effects		84.2128***	110.7053***	116.1006***	114.3871***
Time fixed effects		132.4803***	38.9858***	35.9374***	35.3002***
Adjusted- R^2	0.0003	0.2466	0.4377	0.5696	0.5648
Log-likelihood	270.2756	324.0393	342.0915	358.6266	356.7162
Obs.	116	116	116	116	116

Notes: t statistics in parenthesis. Implied rates in brackets. *: $p < .10$, **: $p < .05$, ***: $p < .01$. W^* denotes the spatially lagged variable.

use of the energy reserves of energy-rich provinces. The spatial autocorrelation coefficient λ is significant, indicating spatial dependence among the residuals.

4. Conclusions and policy recommendations

We have analyzed the convergence of cross-province energy intensity based on a panel data set of 29 Chinese provinces over the period 2003–2015 using the following approaches: σ convergence, kernel density, unconditional and conditional β convergence. The following conclusions have been drawn from our empirical analysis.

First, as indicated by σ convergence analysis, the cross-province energy intensity gap has narrowed throughout the sample period, with a short, yet explainable, interruption in 2011. The generic downward trend coincided with varied rates of energy intensity levels for provinces, as suggested by the dynamics of various percentiles. In particular, the analysis showed that the energy intensity declined more rapidly in high-level provinces than in the other provinces. Apparently, this situation has caused a narrowing effect on the overall energy intensity gap among provinces. Convergence also followed from the estimated kernel densities, which indicated a steepening and narrowing of the distribution of energy intensity over time.

Narrowing the regional differentials is a policy handle in the context

of reducing the overall (e.g., national) energy intensity in that it makes it possible to pick the low hanging fruit (Zhang and Broadstock, 2016). Specifically, for the provinces that have already substantially reduced their energy intensity, it becomes increasingly difficult to further reduce their energy intensity. A way out of this problem is to reduce the energy intensity in provinces with relatively high energy intensity. This solution is based on the assumption that the energy intensity in provinces with high energy intensity decreases faster than that in provinces with low energy intensity (Zhao et al., 2015). An additional advantage of this policy is that in the lagging provinces, it may improve environmental conditions, stimulate economic development and contribute to a more balanced population growth.

As a follow up of the trend, we analyzed the determinants of convergence. According to β convergence, the revealed convergence among provinces was hardly unconditional, owing to their large disparity in economic structures. As a further verification of its conditional nature, convergence was tested by using two types of models, viz. a model with two-way fixed effects only and a model controlling for their own determinants and their spatial lags. While the first model revealed significant conditional convergence, the second model revealed even stronger conditional convergence because bias of the estimator of β was reduced. The main conclusions are the following.

FDI has played an important role in reducing energy intensity.

Table 5Three-year β convergence models of energy intensity with geographic distance spatial weights matrix.

Independent Variables	Unconditional model	Conditional model without controls	Conditional model with controls	Conditional initial model with spillovers	Conditional final model with spillovers
$\ln EI_{t-1} (\beta)$	0.0009 (0.1777)	− 0.1455*** (− 5.1713)	− 0.1520*** (− 5.8404)	− 0.2195*** (− 8.0215)	− 0.2183*** (− 7.9897)
Implied rate: γ	[− 0.0003]	[0.0524]	[0.0550]	[0.0826]	[0.0821]
$\ln GPPC$			− 0.1550*** (− 4.4409)	− 0.1397*** (− 4.4640)	− 0.1391*** (− 4.7040)
$\ln Secondsec$			0.0754*** (2.3888)	0.0578** (2.0718)	0.0644** (2.4380)
$\ln FDI$			− 0.0111*** (− 2.8043)	− 0.0093*** (− 2.4638)	− 0.01060*** (− 3.0300)
$\ln Enresc$			0.0046 (0.7244)	0.0021 (0.3450)	
$\ln Caplaborratio$			− 0.0067 (− 0.4930)	0.0038 (0.3083)	
$\ln Invest$			0.0386*** (2.7404)	0.0336*** (2.6252)	0.0346*** (3.0300)
$W^* \ln GPPC$				− 0.1549** (− 2.1292)	− 0.2027*** (− 3.4451)
$W^* \ln Secondsec$				0.1750*** (2.7950)	0.1480*** (2.5184)
$W^* \ln FDI$				− 0.0293*** (− 3.5303)	− 0.0305*** (− 3.7770)
$W^* \ln Enresc$				0.0240* (1.8225)	0.0270** (2.1755)
$W^* \ln Caplaborratio$				− 0.0345 (− 1.1591)	
$W^* \ln Invest$				0.0847*** (3.0471)	0.0664** (2.8190)
Constant	− 0.0218* (− 1.8997)	0.0303*** (2.7530)	1.0992*** (3.8374)	1.5219*** (2.0792)	2.0682*** (4.5334)
λ	0.8140*** (12.5246)	0.1628 (0.6602)	− 0.1931 (− 0.6209)	0.0353 (0.1297)	0.0963 (0.3697)
Spatial fixed effects		84.2128***	110.7053***	116.1006***	114.3871***
Time fixed effects		132.4803***	38.9858***	35.9374***	35.3002***
Adjusted- R^2	0.0003	0.2466	0.4438	0.5773	0.5695
Log-likelihood	271.5373	321.1272	339.5555	354.8619	353.6907
Obs.	116	116	116	116	116

Notes: t statistics in parenthesis. Implied rates in brackets. *: $p < .10$, **: $p < .05$, ***: $p < .01$. W^* denotes the spatially lagged variable.

Hence, in the coming Five-Year Plan, more FDI inflow into China should be encouraged through more targeted economic policies. However, due to ownership issues, the current FDI inflows into sectors such as mining, construction, and financial intermediation are still highly restricted by the central government. Notably, the mining industry comprises a major part of the economies in many western provinces. Apparently, its technological advancement will help bridge the technological gap and greatly improve the cross-province convergence in energy intensity.

To reduce the overall energy intensity and reverse environmental degradation, new clean technologies must be developed as a nationwide priority and adopted in all industrial production processes. However, the analysis has shown that, to date, the substitution of energy-intensive for low-energy vintages has not taken off. Several policy instruments for achieving this goal including licenses and permits, ambient quality standards, emission standards, product standards, subsidies, planning and land, are available (for an overview, see Barde, 2010). In addition, due to the rapid increase in energy costs, the wealthy eastern provinces should consider significant economic restructuring by transferring conventional industries (e.g., the energy-intensive steel industry) to high value-added industries (e.g., the information industry). However, the nationwide industry shift must be

guided by the central government from a strategic perspective to avoid the overconcentration of, inter alia, energy-intensive industries in certain energy-rich provinces.

One important policy handle for improving both overall energy intensity and cross-province convergence is the promotion of international and domestic technology diffusion. International technology transfers from advanced countries were a common practice in the eastern coastal provinces in the early stage of the economic reform. With locational advantages and improved basic infrastructures, these provinces were spearheads for attracting foreign investment and advanced technologies. This channel of acquiring new, clean and energy-efficient technologies from overseas should be kept wide open so that these provinces can act as an important technology base for internalizing the newest knowledge and developments from advanced countries. Domestic technology diffusion, on the other hand, focuses on indigenous technology transfer mainly from the coastal east to the inland west. Hence, policies (e.g., tax relief, land grant) for encouraging the coastal east to work together with the inland west should be designed and implemented.

Indigenous innovation is of most importance for developing domestic innovation capabilities. Only if China exhibits substantial domestic innovation capabilities, it may be able to absorb international technology and

knowledge more effectively and efficiently. International technology transfer and indigenous innovation distribution must interact to create spatial spillovers to reduce energy intensity. In summary, to not only narrow the energy intensity gap across provinces but also to reduce the overall energy intensity, policies aimed at facilitating technology diffusion through FDI and indigenous investment should be encouraged. Additionally, as part of diffusion efforts, government policies should pay special attention to financial incentives for energy-efficiency investment, energy-efficiency education and training, and demonstration programs.

The 11th Five-Year Plan has been effective in reducing the energy intensity gap among Chinese provinces. For example, in 2004, the National Development and Reform Commission issued the "*medium- and long-term energy conservation plan*," which took energy intensity reduction as the highest priority. The plan established specific targets for energy-intensive industries in energy-abundant provinces to reduce their energy intensity, helping energy-intensive provinces catch up with low energy-intensive provinces. In 2006, the Chinese central govern-

ment enforced the shutdown of nationwide small-scale coal-fired power plants. As a result, million tons of energy were saved, which has helped reduce the overall energy intensity every year. Efforts devoted to reducing energy intensity and the gaps among provinces may also depend on various regulations, laws and market measures. For example, China's first environmental protection tax law, taking effect on 1 January 2018, will have a great impact on highly energy-intensive and heavily polluting industries in certain western provinces. The law may further narrow the energy intensity gap among Chinese provinces.

Acknowledgements

The authors are grateful to the financial support provided by the National Natural Science Foundation of China (Nos. 71573119 and 71625005), and Humanities and Social Science Research Program of the Ministry of Education (No. 17YJC790061).

Appendix A. σ convergence and kernel density

We first analyze σ convergence by means of the development of the standard deviation of energy intensity in levels. The result is presented in Fig. A.1, which shows an overall downward trend in the dispersion of energy intensity over the period 2003–2015. The annual standard deviation of energy intensity decreased from 0.8982 in 2003 to 0.7043 in 2010. In 2010–2011, however, there was an increase, immediately followed by a downward movement during the period 2011–2015.

Fig. A.1 also shows that during the period 2003–2010, the energy intensity gap across Chinese provinces narrowed, as stipulated in the 11th Five-Year Plan for the period (2006–2010). The upsurge at the beginning of the 12th Five-Year Plan (the year 2011) is most likely because energy-rich provinces boosted their economic growth to improve their political performance at the expense of energy intensity improvement. We also note that in the second half of 2011, each province's specific energy policy target (including its reduction target), as specified in the 12th Five-Year Plan, started to be implemented. Apparently, the implementation accompanied a further decline in the standard deviation. To conclude, Fig supports σ convergence.

Fig. A.1. Standard deviation of energy intensity, 2003–2015.

Fig. A.2a presents the dynamics of the 10th, 25th, 50th, 75th, and 90th percentiles of energy intensity for the period 2003–2015. Each percentile shows a downward trend. Among them, the 90th percentile shows the strongest decline and the 10th and 25th percentiles the weakest, indicating that high energy intensity provinces reduced their intensity more than did low energy intensity provinces.

Fig. A.2. (a) Energy intensity dynamics of the 10th, 25th, 50th, 75th, and 90th percentile. (b) Energy intensity dynamics of the 90-10 and 75-25 IQRs.

Fig. A.2b presents the dynamics of inter-quantiles (IQR) (90-10) and IQR (75-25). Over the entire period, the former decreased from 2.7123 in 2003 to 1.8886 in 2015, except between 2004 and 2007, when it was constant, as well as between 2012 and 2014, when it rose sharply. IQR (75-25) shows a different development. It increased slightly from 0.9632 in 2003 to 1.0429 in 2005 before declining to 0.4994 in 2015. The different developments of the two IQRs reflect the differences in energy policy by the central government. Before 2005, it had not implemented an energy intensity reduction policy. Consequently, the energy intensity gap between provinces with high and low energy intensity changed. Because of the introduction of energy intensity targets for each province in 2006 in the 11th Five-Year Plan, the gap gradually narrowed, which suggests that the policy has been effective.

Fig. A.3 displays the estimated kernel density distributions for 2003, 2007, 2011, and 2015. It shows that the distributions of cross-province energy intensity became more compact and steeper, indicating convergence. In particular, the peak of the distribution gradually moved to the left and simultaneously increased, implying that the annual average energy intensity had declined over time and that there had been convergence. Furthermore, the upper tail of the distributions decreased over time, implying that provinces with high energy intensity had improved.

Fig. A.3. Estimated kernel density for energy intensity, 2003, 2007, 2011, 2015.

Appendix B

Table B.1 shows the modeling results for 1, 2 and 3-year intervals. For the 2-year interval model, the coefficient $\beta = -0.0738$ is significant and negative as well as larger than that of the 1-year interval model (-0.2447). For the 3-year interval model, the coefficient $\beta = -0.2332$ is also significant and negative as well as larger than that of the 1-year interval model (-0.2447) and smaller than that of the 2-year interval model

Table B.1

The final models for one-, two-, and three-year intervals.

Independent Variables	1-year interval	2-year interval	3-year interval
$\ln EI_{t-1} (\beta)$	-0.2447^{***} (-8.5016)	-0.0738^{***} (-6.4132)	-0.2332^{***} (-8.9192)
Implied rate: γ	[0.1403]	[0.0256]	[0.0664]
$\ln GPPc$	-0.1284^{***} (-4.6110)	-0.0505^{***} (-4.2328)	-0.1376^{***} (-4.7112)
$\ln Secondsec$			0.0685^* (2.6748)
$\ln FDI$	-0.0096^{***} (-2.5138)		-0.0110^{***} (-3.1142)
$\ln Enresc$			
$\ln Caplaborratio$			
$\ln Invest$	0.0482^{***} (3.7513)	0.0142^{***} (2.5429)	0.0352^{***} (3.0966)
$W^* \ln GPPc$			-0.2180^{***} (-3.6470)
$W^* \ln Secondsec$	0.2232^{***} (3.3410)	0.0956^{***} (3.3753)	0.1625^{***} (2.7089)
$W^* \ln FDI$	-0.0341^{***} (-3.8722)	-0.0098^{***} (-2.8828)	-0.0317^{***} (-3.7594)
$W^* \ln Enresc$			0.0226^* (1.6763)
$W^* \ln Caplaborratio$	-0.1170^{**} (-3.9533)	-0.0430^{***} (-3.5181)	
$W^* \ln Invest$	0.1066^{***} (3.2611)	0.0419^{**} (3.0106)	0.0587^{**} (2.4021)
Constant	0.0721 (0.2177)	-0.0035 (-0.0239)	2.1824^{***} (4.8715)
λ	0.2841^{**} (4.2897)	0.0148 (0.1386)	0.2950^{***} (2.5916)
Adjusted-R ²	0.2379	0.3280	0.5676
Log-likelihood	768.7445	601.9726	354.4139
Obs.	348	174	116

Notes: t statistics in parenthesis. Implied rates in brackets. *: $p < .10$, **: $p < .05$, ***: $p < .01$. Definitions of the variables in Table 1. W^* denotes the spatially lagged variable. $W_{ij} = 1$ if two provinces share a common border, 0 otherwise; $W_{ii} = 0$.

(-0.0738). The implied rate of convergence of the 3-year interval model is 0.0885, which is smaller than that of the 1-year interval model and larger than that of the 2-year interval model.

Apart from β and γ , the three models have different significant explanatory variables. In particular, $LnSecondsec$, $LnEnresc$, $LnCaplaborratio$, $W*LnGPPc$ and $W*LnEnresc$ in the 1-year interval Initial model are insignificant, whereas the 2-year interval model has one more insignificant explanatory variable than the 1-year interval model, namely, $LnFDI$. Most importantly, the spatial autocorrelation coefficient λ in the 2-year interval model is insignificant.

References

- Andrews-Speed, P., 2009. China's ongoing energy efficiency drive: origins, progress and prospects. *Energy Policy* 37 (4), 1331–1344.
- Barde, J.P., 2010. Environmental policy and policy instruments. In: Folmer, H., Gabel, H.L. (Eds.), *Principles of Environmental and Resource Economics: A Guide for Students and Decision-Makers*. Edward Elgar, Aldershot.
- Barro, R.J., 1991. Economic growth in a cross section of countries. *Q. J. Econ.* 106 (2), 407–443.
- BP, 2013. *Statistical Review of World Energy 2013*.
- Burnett, J.W., 2016. Club convergence and clustering of energy-related CO₂ emissions. *Resour. Energy Econ.* 46, 62–84.
- Burnett, J.W., Madariaga, J., 2016. The convergence of US state-level energy intensity. *Energy Econ.* 62, 357–370.
- Cheung, K.Y., Lin, P., 2004. Spillover effects of FDI on innovation in China: evidence from the provincial data. *China Econ. Rev.* 15 (1), 25–44.
- Cole, M.A., Rayner, A.J., 2000. The Uruguay Round and air pollution: estimating the composition, scale and technique effects of trade liberalization. *J. Int. Trade Econ. Dev.* 9 (3), 339–354.
- Elhorst, J.P., 2014. *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*. Springer, Berlin Heidelberg.
- Elliott, R.J., Sun, P., Chen, S., 2013. Energy intensity and foreign direct investment: a Chinese city-level study. *Energy Econ.* 40, 484–494.
- Filippini, M., Zhang, L., 2016. Estimation of the energy efficiency in Chinese provinces. *Energy Effic.* 9 (6), 1315–1328.
- Folmer, H., Oud, J., 2008. How to get rid of W: a latent variables approach to modeling spatially lagged variables. *Environ. Plan. A* 40 (10), 2526–2538.
- Herrerias, M.J., 2012. World energy intensity convergence revisited: a weighted distribution dynamics approach. *Energy Policy* 49, 383–399.
- Herrerias, M.J., Liu, G., 2013. Electricity intensity across Chinese provinces: new evidence on convergence and threshold effects. *Energy Econ.* 36, 268–276.
- Herrerias, M.J., Orts, V., 2010. Is the export-led growth hypothesis enough to account for China's growth? *China World Econ.* 18 (4), 34–51.
- Herrerias, M.J., Joyeux, R., Girardin, E., 2013. Short-and long-run causality between energy consumption and economic growth: evidence across regions in China. *Appl. Energy* 112, 1483–1492.
- Huang, B., Meng, L., 2013. Convergence of per capita carbon dioxide emissions in urban China: a spatio-temporal perspective. *Appl. Geogr.* 40, 21–29.
- Hübner, M., Keller, A., 2010. Energy saving via FDI? Empirical evidence from developing countries. *Environ. Dev. Econ.* 15 (01), 59–80.
- Islam, N., 1995. Growth empirics: a panel data approach. *Q. J. Econ.* 110 (4), 1127–1170.
- Islam, N., 2003. What have we learnt from the convergence debate? *J. Econ. Surv.* 17 (3), 309–362.
- Jiang, L., Folmer, H., Ji, M., 2014. The drivers of energy intensity in china: a spatial panel data approach. *China Econ. Rev.* 31, 351–360.
- Jiang, L., Zhou, H.F., Bai, L., Zhou, P., 2017. Does foreign direct investment drive environmental degradation in China? An empirical study based on air quality index from a spatial perspective. *J. Clean. Prod.*
- Jiang, Z., Lin, B., 2012. China's energy demand and its characteristics in the industrialization and urbanization process. *Energy Policy* 49, 608–615.
- Kiran, B., 2013. Energy intensity convergence in OECD countries. *Energy Explor. Exploit.* 31 (2), 237–248.
- Kelejian, H.H., Piras, G., 2014. Estimation of spatial models with endogenous weighting matrices, and an application to a demand model for cigarettes. *Region. Sci. Urban Econ.* 46, 140–149.
- Komen, M.H., Gerking, S., Folmer, H., 1997. Income and environmental R&D: empirical evidence from OECD countries. *Environ. Dev. Econ.* 2 (4), 505–515.
- Le Pen, Y., Sévi, B., 2010. On the non-convergence of energy intensities: evidence from a pair-wise econometric approach. *Ecol. Econ.* 69 (3), 641–650.
- LeSage, J., Pace, R.K., 2009. *Introduction to Spatial Econometrics*. CRC Press, Boca Raton, FL, USA.
- Liddle, B., 2009. Electricity intensity convergence in IEA/OECD countries: aggregate and sectoral analysis. *Energy Policy* 37 (4), 1470–1478.
- Liddle, B., 2010. Revisiting world energy intensity convergence for regional differences. *Appl. Energy* 87 (10), 3218–3225.
- Lin, G., Long, Z., Wu, M., 2005. A spatial analysis of regional economic convergence in China: 1978–2002. *China Econ. Q.* 4 (Suppl. 10), S67–S82.
- Markandya, A., Pedrosa-Galinato, S., Streimikiene, D., 2006. Energy intensity in transition economies: is there convergence towards the EU average? *Energy Econ.* 28 (1), 121–145.
- Metcalfe, G.E., 2008. An empirical analysis of energy intensity and its determinants at the state level. *Energy J.* 1–26.
- Miketa, A., Mulder, P., 2005. Energy productivity across developed and developing countries in 10 manufacturing sectors: patterns of growth and convergence. *Energy Econ.* 27 (3), 429–453.
- Mulder, P., De Groot, H.L.F., 2007. Sectoral energy and labor productivity convergence. *Environ. Resour. Econ.* (36), 85–112.
- Pan, X., Liu, Q., Peng, X., 2015. Spatial club convergence of regional energy efficiency in China. *Ecol. Indic.* 51, 25–30.
- Pettersson, F., Maddison, D., Acar, S., Söderholm, P., 2014. Convergence of carbon dioxide emissions: a review of the literature. *Int. Rev. Environ. Resour. Econ.* 7 (2), 141–178.
- Song, F., Zheng, X., 2012. What drives the change in China's energy intensity: combining decomposition analysis and econometric analysis at the provincial level. *Energy Policy* 51, 445–453.
- Stern, D.I., Jotzo, F., 2010. How ambitious are China and India's emissions intensity targets? *Energy Policy* 38 (11), 6776–6783.
- Suri, V., Chapman, D., 1998. Economic growth, trade and energy: implications for the environmental Kuznets curve. *Ecol. Econ.* 25 (2), 195–208.
- Yao, L., Chang, Y., 2014. Energy security in China: a quantitative analysis and policy implications. *Energy Policy* 67, 595–604.
- Yu, H., 2012. The influential factors of China's regional energy intensity and its spatial linkages: 1988–2007. *Energy Policy* 45, 583–593.
- Zhang, D., Broadstock, D.C., 2016. Club convergence in the energy intensity of China. *Energy J.* 37, 137–158.
- Zhang, W., Pan, X., Yan, Y., Pan, X., 2017. Convergence analysis of regional energy efficiency in china based on large-dimensional panel data model. *J. Clean. Prod.* 142, 801–808.
- Zhao, X., Burnett, J.W., Lacombe, D.J., 2015. Province-level convergence of China CO₂ emission intensity: a spatial dynamic panel data analysis. *Appl. Energy* 150, 286–295.
- Zheng, Y., Qi, J., Chen, X., 2011. The effect of increasing exports on industrial energy intensity in China. *Energy Policy* 39 (5), 2688–2698.
- Zhou, P., Ang, B.W., 2008. Linear programming models for measuring economy-wide energy efficiency performance. *Energy Policy* 36, 2911–2916.
- Zhou, P., Ang, B.W., Zhou, D.Q., 2012. Measuring economy-wide energy efficiency performance: a parametric frontier approach. *Appl. Energy* 90 (1), 196–200.