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## Peer effect, political competition, and eco-efficiency: Evidence from city-level data in the People's Republic of China

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## **ADB Working Paper Series**

### **PEER EFFECT, POLITICAL COMPETITION, AND ECO-EFFICIENCY: EVIDENCE FROM CITY-LEVEL DATA IN THE PEOPLE'S REPUBLIC OF CHINA**

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and Yantuan Yu

No. 1125  
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**Abstract**

This study examines the impacts of political competition on eco-efficiency. We first develop a theoretical model in which local government officials compete against each other to maximize their own political score. We find that after an initial stage of decline, eco-efficiency eventually turns upwards, once environmental performance becomes a meaningful component of local government officials' annual assessment. Eco-efficiency also exhibits a pattern of convergence. Lastly, level of political competition is found to be negatively correlated with eco-efficiency. For the empirical analysis, we use a data envelopment analysis (DEA) model to compute the eco-efficiency level for 191 Chinese cities from 2003 to 2015. Our empirical evidence presents a U-shape pattern in the trend of eco-efficiency, and helps us identify two peer effects that work in opposite directions for cities and regions: the incentivizing effect arising from higher performing neighbors, and the disincentivizing effect when a city outperforms its competitors. Both peer effects lead to convergence in eco-efficiency, and our spatial econometric modeling analysis suggests that the net peer effect is significantly positive. We also find evidence of political competition reducing eco-efficiency, as predicted in the theoretical model. Our findings are robust to alternative measures of eco-efficiency.

**Keywords:** peer effect, political competition, eco-efficiency, spatial analysis, People's Republic of China

**JEL Classification:** C61, C67, Q56, R15

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# 1. INTRODUCTION

The relationship between economic growth and the environment remains controversial, and has received increasing attention due to the escalated level of environmental risk today.<sup>1</sup> Over time, it becomes evident that economic growth tends to occur conjointly with environmental degradation. Numerous academicians and policy makers have contemplated the issue of how to engineer a transition away from unsustainable growth to eventual sustainable development. Eco-efficiency,<sup>2</sup> the concept of producing more goods and services while using fewer resources and creating less waste and pollution, has been proposed as an indicator by which to monitor such a transition (Schmidheiny and Timberlake 1992; World Business Council for Sustainable Development 1992; OECD 2002; United Nations 2009). At the same time, strategic interactions across regions regarding environmental issues is unavoidable, due to the ability of local environmental policy to influence capital and population flows across sub-jurisdictions.<sup>3</sup> Against this backdrop, this paper investigates the evolution of eco-efficiency over time, and assesses its association with peer effects and sub-jurisdiction political competition.

We first build a simple theoretical model of political competition among regional government officials, each of whom allocates resources between economic production and environmental protection. Our comparative statics analysis suggests that eco-efficiency is negatively correlated with pollution intensity, and positively correlated with financial endowment and political emphasis on the environment. This means that as long as income increases, technology improves, and policy becomes environmentally friendlier, the level of eco-efficiency is expected to increase steadily over time. This is assuming, however, that environmental performance is a meaningful component of annual political assessment; otherwise, political competition would simply lead to a continual decline in eco-efficiency in a race-to-the-bottom fashion. This helps to explain the U-shape in the historical trend of eco-efficiency in countries that experience drastic changes in environmental policy and attitude. We also identify a pattern of convergence in the trends of eco-efficiency. Last, we find that a heightened level of political competition reduces eco-efficiency, while its impact on the rate of convergence varies depending on the different causes of convergence.

The People's Republic of China (PRC) provides a compelling setting to investigate this environmental issue. As the fastest-growing major economy in recent decades, the PRC has surged ahead of the rest of the world in terms of material consumption (e.g., construction minerals, metal ores, fossil fuels, biomass), creating intense environmental pressures, but at the same time it has remained among the most successful in improving its resource efficiency (UNDP 2013). While its growth has lifted millions out of poverty, it has also come with rising environmental challenges, such as deteriorating water quality, deforestation, and pollution, as well as frequent haze. In the PRC, the tournament competition among city leaders is an important feature of its political system (Xu 2011) which has motivated local authorities to compete with one another to facilitate rapid economic growth (Maskin, Qian, and Xu 2000; Li and Zhou 2005; Yu et al. 2016). However, as pollution is becoming one of the PRC's greatest

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<sup>1</sup> This body of research, known as the environmental Kuznets curve (EKC) literature, has been enormously influential. The work by Grossman and Krueger (1995) is widely regarded as one of the earliest attempts at EKC hypotheses. An extensive overview of theoretical studies and empirical evidence regarding EKC can be found in Kaika and Zervas (2013).

<sup>2</sup> The term "eco-efficiency" is a concept and philosophy geared toward sustainability, combining ecological and economic efficiency.

<sup>3</sup> The pollution haven hypothesis was first developed by Pethig (1976) and McGuire (1982), and later improved by Copeland and Taylor (1994) and Levinson and Taylor (2008), among others.

threats – especially to health – the country’s government has introduced a series of regulatory policies in recent decades. Although success has not occurred immediately,<sup>4</sup> it seems that the desired turnaround has eventually occurred.

For our empirical work, we use a data envelopment analysis (DEA) model to compute the eco-efficiency levels of 191 Chinese cities at and above the prefecture level between 2003 and 2015. The evolution in eco-efficiency in the PRC exhibited a U-shaped pattern during that period, with the rapid upward trend occurring from around 2013. We also examine heterogeneous patterns across different types of cities. Spatial econometric modeling analysis suggests that the net peer effect is significantly positive. Specifically, without consideration of political competition, a city would see its eco-efficiency decrease by 0.240% triggered by a 1% increase in its lower performing neighbors, but an increase by 0.775% with a 1% increase in its higher performing neighbors. In addition, the positive net peer effect holds significantly in heterogeneous groups.

We then investigate the effects of strategic political competition on eco-efficiency. In particular, we focus on how a city’s eco-efficiency is affected by its neighboring cities’ eco-efficiency in two different scenarios: with and without the consideration of political competition. Our results show that in the presence of political competition, the peer effects (both disincentivizing and incentivizing effects) were amplified during the years 2003–2010, and attenuated during the years 2011–2015 as well as across the period as a whole. Our findings are robust to alternative measures of eco-efficiency.

This study extends several strands of literature. First, productivity efficiency has been broadly used to measure environmental performance in the existing literature (Zhou et al. 2017) and DEA has been widely used to construct multi-factor measures of eco-efficiency (Mahlberg and Luptacik 2014). To accurately quantify the growth-environment nexus and estimate eco-efficiency, we develop a comprehensive DEA model that simultaneously incorporates a non-convex metafrontier (O’Donnell et al. 2008; Tiedemann et al. 2011; Huang et al. 2013; Afsharian 2017; Afsharian and Podinovski 2018; Walheer 2018), super-efficiency (Andersen and Petersen 1993), and undesirable outputs (Tone 2003) into a modified slacks-based measure (MSBM) (Sharp et al. 2007). The strengths of our model comprise its comparable treatment of the efficiency of the same decision-making unit (DMU) in different years due to technological progress when considering the non-convex metafrontier, its identifiable treatment of DMUs located on efficient frontier to employ super-efficiency, its comprehensive treatment of DMUs’ slacks improvement in using MSBM, and its similarity to the real production process as regards undesirable outputs. Non-parametric DEA techniques or activity models make it possible to incorporate several environmental pressures as well as to measure eco-efficiency at specific environmental pressure levels. Ideally, measuring eco-efficiency for sub-jurisdictions within a country requires disaggregated data on inputs and outputs, which are usually unavailable in most

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<sup>4</sup> For example, in its National 10th Five-Year Plan (2001–2005), released in 2001, the central government for the first time added environmental protection and pollution reduction to its list of “national strategic goals,” and set a target to reduce pollutant discharges by 10% by the end of 2005. Under the new regulation framework, each province was assigned a specific target, and the provincial government officials were to be evaluated on, among other things, how well these targets were met. However, little improvement in environmental quality has been observed in the PRC based on data between 1998 and 2008, because the pollution mandates imposed by the central government have triggered strategic polluting responses from the provinces (Cai, Chen, and Gong 2016).

developing countries. The unique city-level input and output data enable us to fill this gap in the Chinese context.<sup>5</sup>

Second, this study sheds new light on the ongoing research on environmental convergence. The concept of convergence, which has been adopted to assess whether poorer regions are able to catch up with relatively richer regions over time, has recently been extended to the study of environmental issues.<sup>6</sup> In theory, environmental convergence can be justified by income convergence and the environmental Kuznets curve (EKC). Given an inverted-U relation between income and emission (Grossman and Krueger 1995), environmental convergence is a plausible prediction if the low-income region in question exhibits a superior economic growth rate to its high-income counterpart. The existing research mainly focuses on testing the convergence of emission intensity (List 1999; Strazicich and List 2003; Ezcurra 2007; Romero-Avila 2008; Jobert, Karanfil, and Tykhonenko 2010) or energy efficiency (Mielnik and Goldemberg 2000; Markandya et al. 2006; Liddle 2009, 2010; Jaunky 2013; Meng et al. 2013), for which the approaches of unit root test and log-t test (Phillips and Sul 2007) have been widely adopted. However, most of these studies have only accounted for the environmental side of production processes (such as per capita emissions), and have only considered a single emission to represent the environmental impact of economic activity. Camarero et al. (2013) have attempted to measure eco-efficiency using the DEA model as well as to investigate its convergence across OECD countries. We extend this strand of literature by investigating the convergence of eco-efficiency in a sub-national jurisdiction context of the PRC, for which achieving a good balance between economic growth and environmental sustainability is of critical importance given the sheer size of economy and resource usage in this country.

Moreover, we innovatively apply the two-regime spatial Durbin model to capture the peer effect on the convergence of eco-efficiency. A branch of the existing literature focuses on the “spillover effect” by examining differences in pollution levels or health outcomes between border and interior jurisdictions (Helland and Whitford 2003; Gray and Shadbegian 2004; Kahn 2004; Cai et al. 2016; Chen and Huang 2016). We incorporate the geographic spillover of eco-efficiency by including the attributes of neighboring regions. Indeed, a city’s eco-efficiency depends not just on its own attributes, but also on those of its peers. Failure to account for geographic spillovers in empirical analyses of eco-efficiency may lead to biased inferences. We find that the evolution of regional eco-efficiency depicts an interesting pattern of dynamics. Witnessing the excellent performance of its outstanding neighbors, a city is incentivized to catch up, leading to improvements in eco-efficiency. However, when a city outperforms its neighbors, its eco-efficiency improvement tends to slow down, perhaps due to complacency. This finding is important in that it predicts a pattern of convergence among different regions with different levels of eco-efficiency.

Our analysis integrates political competition into the analysis of eco-efficiency. Strategic horizontal interaction among local governments has represented one of the main foci of public economics. Researchers generally find that for regions within a country, cross-

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<sup>5</sup> For example, one can collect the PRC’s provincial energy intensity data from the National Bureau of Statistics, but information on the country’s urban energy intensity is not consistently reported. The PRC’s urban energy consumption will be overestimated if we multiply provincial energy intensity statistics and prefecture gross domestic product (GDP). To overcome this shortcoming, Huang et al. (2018) have collected the PRC’s urban energy intensity and have estimated primary energy consumption using a bottom-up rather than a top-down approach.

<sup>6</sup> The neoclassical growth theory developed by Solow (1956) predicts that a region’s growth rate in per capita income is inversely related to its initial per capita income, suggesting that poorer regions will catch up with relatively richer regions over time. A thorough review of the various definitions of convergence and approaches to testing it can be found in Islam (2003).



border fiscal competition exists (Besley and Case 1992; Geys and Osterloh 2013; Janeba and Osterloh 2013; Agrawal 2015; Yu et al. 2016), with the degree of strategic interaction being more pronounced if governors are politically sensitive to fiscal policy changes in neighboring jurisdictions, and less pronounced if they are not (Elhorst and Freret 2009). Recently, the theory on regional strategic competition has been extended to investigate environmental issues, given the ability of local environmental policy to influence flows of capital and population across sub-jurisdictions. The allocation of authority over environmental decision making within a federal political system has also been discussed, deliberated, and agonized over for decades (Millimet 2013). Nevertheless, the debate cannot be settled without solid empirical evidence. Fredriksson and Millimet (2002) and Fredriksson et al. (2004) have provided evidence that the states of the United States set environmental regulations strategically based on the regulation of neighboring states. This paper extends the existing research by highlighting the impact of political competition on the convergence of eco-efficiency within a country.

Our study provides both new theoretical extension and empirical evidence to the existing research on incentivizing bureaucrats with concrete evaluation criteria. The evaluation system and its impacts on the behavior of local government officials have constituted one of the main foci of public management literature (OECD 1994; Hood 2007). However, despite this topic's importance, empirical evidence has remained mixed at best. Lockwood and Porcelli (2013) have shown that the comprehensive performance assessment system in England has enhanced the quality of public services, although no significant effect on efficiency has been discovered. By contrast, Rasul and Rogger (2015, 2018) claim that concrete targets tend to reduce public service delivery in Nigeria. Our theoretical model projects that without integrating environmental performance into governors' evaluations, political competition inevitably leads to continual deterioration in environmental quality. The results of our empirical analysis echo these theoretical predictions by exhibiting the effectiveness of including environmental factors into the assessment system, altering the pattern of eco-efficiency over time.

The remainder of this paper is organized as follows. Section 2 outlines our theoretical model, followed by a description of the methodology and the data in Section 3. In Section 4, we present and discuss the results. Section 5 concludes the paper.

## 2. THE THEORETICAL MODEL

We build a simple model in which there are  $N$  regions, each headed by a government official whose objective function is as follows:

$$U_i = U(y_i, P_i), \quad (1)$$

where  $y_i$  is the GDP in region  $i$ , and  $P_i$  is the local official's probability of political promotion at the end of the year. It is reasonable to assume that

$$\frac{\partial U}{\partial y} > 0, \frac{\partial U}{\partial P} > 0. \quad (2)$$

For the sake of simplicity, we do not consider factors such as corruption and bribery for political promotion, and instead assume a meritocratic process of competition among all  $N$  local officials. The annual assessment is conducted by the higher government, which will then assign to each local official a score that considers both economic and environmental performance, the latter being measured in terms of regional environmental quality,  $q_i$ . We believe that it is reasonable to assume that, all else being

equal, the probability of promotion diminishes for each local official when the number of competitors increases for the same position. Thus, we can use the following equation and properties:

$$P_i = P(y_i, q_i; N), \quad (3)$$

$$\frac{\partial P}{\partial y} > 0, \frac{\partial P}{\partial q} > 0, \frac{\partial P}{\partial N} < 0. \quad (4)$$

It is worth noting that, in a sense, GDP is included in the overall utility function twice. This is not unrealistic in the PRC, as GDP has always been of paramount importance for any region and its official, both politically and economically, formally and informally. For the sake of computational simplicity, from this point on we adopt specific function forms as follows:

$$U_i = y_i P_i, \quad (1')$$

$$P_i = y_i^{\frac{\alpha}{N}} q_i^{\frac{\beta}{N}}. \quad (3')$$

Hence, we have:

$$U_i = U(y_i, P(y_i, q_i)) = y_i^{1+\alpha/N} q_i^{\beta/N}. \quad (5)$$

We now define the budget constraint for region  $i$  as represented below:

$$m_i = y_i + a_i, i = 1, 2, \dots, N. \quad (6)$$

The budget,  $m_i$ , for each region is exogenously given. Each local official allocates the available funds between economic growth and environmental protection. The production of “output,”  $y_i$ , leads to  $b_i y_i$  units of raw emissions, where the pollution-intensity coefficient  $b_i$  is exogenously given for each region. For example, regions that heavily rely on the coal mining industry have relatively high  $b_i$  compared to regions that focus on tourism. The other choice variable  $a_i$  refers to the degree of pollution abatement applied in region  $i$  to offset raw emissions at a 1:1 ratio, hence the amount of net emissions contributed by region  $i$  is calculated as below:

$$e_i = b_i y_i - a_i. \quad (7)$$

Due to the spatial spillover effect, regional environmental quality is presented as follows:

$$q_i = \tilde{q}_i - r_{ii} e_i - \sum_j r_{ij} e_j, i \neq j. \quad (8)$$

In the above equation,  $\tilde{q}_i$  is the initial level of environmental quality in region  $i$ . It is not directly linked to the current stage of decision-making, and over the course of the year it will deteriorate due to emissions. As suggested in the above equation, pollution emissions do not necessarily stay within the region where they are originally generated, as they can travel across political boundaries and pose environmental damage in a downstream/downwind region. The transboundary coefficient  $r_{ij}$  is interpreted as the proportion of emissions from region  $j$  that travel to region  $i$ , while  $r_{ii}$  represents the proportion of region  $i$ 's own emissions that ultimately remain. In a closed model, we have:

$$r_{ii} + \sum_j r_{ji} = 1. \quad (9)$$

Assuming structural symmetry among regions at equilibrium, we derive the optimum level of GDP production in each region as follows:

$$y_i = \frac{(\alpha+N)(m_i+\tilde{q}_i)}{(b_i+1)(\alpha+N+\beta r_{ii})}. \quad (10)$$

The proof can be seen in Appendix A. Next, we introduce the eco-efficiency for each region,  $ee_i$ , calculated as the “good output” (GDP,  $y_i$ ) minus the “bad output” (emissions,  $e_i$ ), divided by the total cost (budget,  $m_i$ ). We then have the following result:

$$ee_i = \frac{y_i - e_i}{m_i} = \frac{(\alpha+N)(m_i - b_i \tilde{q}_i) + (b_i+1)m_i \beta r_{ii}}{(b_i+1)m_i(\alpha+N+\beta r_{ii})}. \quad (11)$$

A simple round of comparative statics analysis suggests the following results:

$$\frac{\partial ee_i}{\partial m_i} > 0, \quad (12a)$$

$$\frac{\partial ee_i}{\partial b_i} < 0, \quad (12b)$$

$$\frac{\partial ee_i}{\partial \beta} > 0, \quad (12c)$$

$$\frac{\partial ee_i}{\partial \tilde{q}_i} < 0, \quad (12d)$$

The proof is in Appendix A as well. The positive relationship between  $m_i$  and  $ee_i$  as suggested in (12a) explains the higher eco-efficiency level in the affluent regions like eastern/coastal provinces of the PRC, which are wealthier than the central/western provinces. Result (12b) reveals the negative relationship between production pollution intensity and eco-efficiency, hence resource-based (RB) cities with a higher  $b$  would perform worse. Then, in (12c) and (12d), we can see that a higher  $\beta$  or a lower  $\tilde{q}_i$  tends to induce an increase in eco-efficiency. Note that a higher  $\beta$  means that a relatively heavier weight is attached to environmental protection in the process of the annual political assessment, which may be due to either a lower  $\tilde{q}_i$  (historically severe environmental issue) in the region, or the city's considerable importance on the political map. In the PRC, a city can be categorized as a key environmental protection (KEP) city or a two control zone (TCZ) city for either or both of the above-mentioned reasons. Obviously, if a KEP/TCZ city starts with a historical or ongoing environmental issue and hence has a relatively poor eco-efficiency level, the disproportionately high political emphasis placed on environmental protection in this region will cause the eco-efficiency level to grow faster than its non-KEP or non-TCZ counterpart, thus it is expected that it will eventually catch up.

We take another look at the above results and find that they also help to explain the eventual upward trend of eco-efficiency in all areas. So long as over time, income increases, technology improves, policy becomes environmentally friendlier, we can expect the level of eco-efficiency to steadily increase. However, it is important to note that such favorable results only hold true when  $\beta$  takes a positive value, that is, regional environmental performance is given meaningful consideration in the annual political assessment of local governmental officials. Otherwise, the political competition between regional governmental officials would be reduced to a pure GDP contest (barring any

environmental catastrophe), inevitably leading to a race-to-the-bottom type of environmental performance and a steady decline in eco-efficiency. This, combined with the subsequent increase in eco-efficiency, possibly explains the U-shape in the trend of eco-efficiency level over time in countries like the PRC.

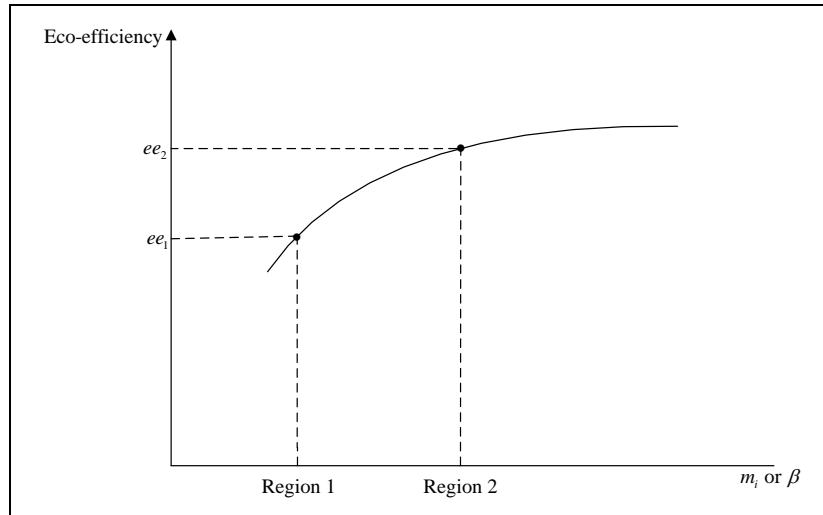
We also find the following results:

$$\frac{\partial^2 ee_i}{\partial m_i^2} < 0, \quad (13a)$$

$$\frac{\partial^2 ee_i}{\partial \beta^2} < 0. \quad (13b)$$

The proof can be found in Appendix A. These results, together with (12), depict a scenario of convergence. Similar to the catch-up effect in international growth theory, whereby countries that start out poorer tend to grow faster than wealthier economies and thus close the gap, we can deduce that regions with a higher eco-efficiency level will slow down, while regions currently with a lower eco-efficiency level will catch up. This effect is illustrated in Figure 1, where the slope of the curves represents the change (increase) rate of the regional eco-efficiency level.

**Figure 1: Eco-efficiency**



We now examine the effects of increased political competition, proxied by a larger  $N$ , attaining the following results:

$$\frac{\partial ee_i}{\partial N} < 0, \quad (12e)$$

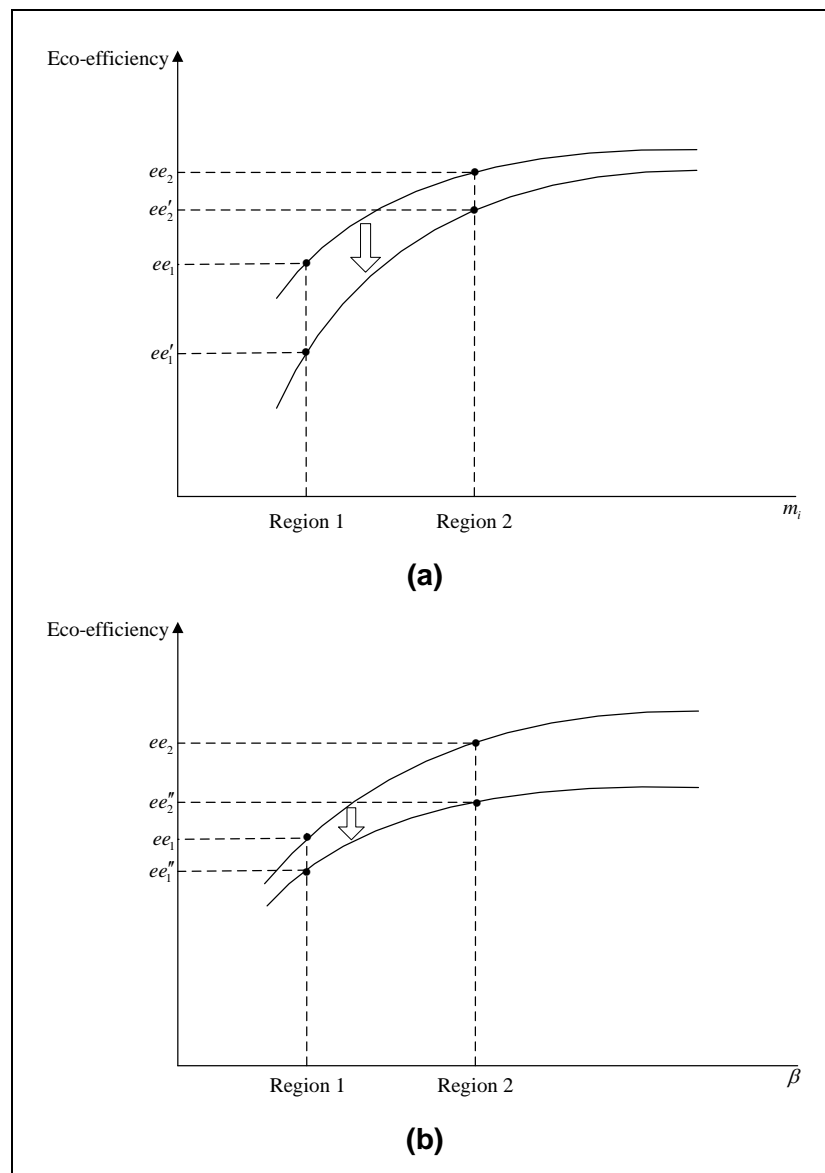
$$\frac{\partial}{\partial N} \left( \frac{\partial ee_i}{\partial m_i} \right) > 0, \quad (14a)$$

$$\frac{\partial}{\partial N} \left( \frac{\partial ee_i}{\partial \beta} \right) < 0. \quad (14b)$$

See Appendix A for the proof. Result (12e) suggests that all else being equal, an increase in political competition leads to a decrease in the eco-efficiency level. Results (14a) and (14b) indicate how the pattern of convergence in eco-efficiency can be affected by heightened political competition in different ways, depending on the causes of

convergence. If convergence is stimulated by a steady economic growth over time, as in Result (14a) and as also illustrated in Figure 2a, an increase in political competition (i.e., a larger  $M$ ) would lead to higher slopes (i.e., respective eco-efficiency increase rates), and as a result a tentatively widened gap between two regions (from  $ee_2 - ee_1$  to  $ee'_2 - ee'_1$ ). However, it seems that this setback would put region 1 in a position where its eco-efficiency level would grow at a faster rate. On the other hand, Result (14b) and Figure 2b suggest that if convergence in eco-efficiency originates from a shift in policy emphasis (increase in  $\beta$ ), then greater political competition may tentatively reduce the eco-efficiency gap (from  $ee_2 - ee_1$  to  $ee''_2 - ee''_1$ ), but convergence may be slowed down in the long run.

**Figure 2: Effects of Political Competition on the Convergence of Eco-efficiency**



### 3. METHODOLOGY AND DATA

#### 3.1 The DEA Model

In this study, eco-efficiency is measured by a DEA model in which there are a total of  $N$  decision-making units (DMUs), i.e., cities. All DMUs are categorized into  $G$  ( $G > 1$ ) heterogeneous groups employing different technologies, and we denote  $N_g$  as the sample size of the  $g$ th group, where  $g = 1, 2, \dots, G$ , apparently resulting in  $\sum_{g=1}^G N_g = N$ . Each DMU uses inputs  $\mathbf{x} = [x_1, x_2, \dots, x_M] \in \mathbb{R}_+^M$  to produce desirable (or good) outputs,  $\mathbf{y} = [y_1, y_2, \dots, y_R] \in \mathbb{R}_+^R$ , and undesirable (or bad) outputs,  $\mathbf{b} = [b_1, b_2, \dots, b_J] \in \mathbb{R}_+^J$ . Assuming variable returns to scale (VRS), the frontier production technology of the  $o$ th DMU in group  $g$  ( $o = 1, 2, \dots, N_g; g = 1, 2, \dots, G$ ) with reference to the group frontier can be expressed as follows:

$$\begin{aligned}
 P^g = & \left\{ (\mathbf{x}_m, \mathbf{y}_r, \mathbf{b}_j) : x_{mg'o} \geq \sum_{n \in g, n \neq o \text{ if } g=g'} \lambda_{gn} x_{mgn}, m = 1, 2, \dots, M; \right. \\
 & y_{rg'o} \leq \sum_{n \in g, n \neq o \text{ if } g=g'} \lambda_{gn} y_{rgn}, r = 1, 2, \dots, R; \\
 & b_{jg'o} \geq \sum_{n \in g, n \neq o \text{ if } g=g'} \lambda_{gn} b_{jgn}, j = 1, 2, \dots, J; \\
 & \left. \sum_{n \in g, n \neq o \text{ if } g=g'} \lambda_{gn} = 1; \lambda_{gn} \geq 0; g = 1, 2, \dots, G; n \in g, n \neq o \text{ if } g = g' \right\}
 \end{aligned} \tag{15}$$

where  $\lambda_{gn}$  is a weighting vector of the  $n$ th DMU in group  $g$  with reference to the corresponding group frontier. After enveloping all group frontier technologies (Battese et al. 2004), non-convex metafrontier production technology can be expressed as follows:

$$\begin{aligned}
 P^{nc-meta} = & \left\{ (\mathbf{x}_m, \mathbf{y}_r, \mathbf{b}_j) : x_{mg'o} \geq \sum_{g=1}^G \sum_{n \in g, n \neq o \text{ if } g=g'} \gamma_{gn} x_{mgn}, m = 1, 2, \dots, M; \right. \\
 & y_{rg'o} \leq \sum_{g=1}^G \sum_{n \in g, n \neq o \text{ if } g=g'} \gamma_{gn} y_{rgn}, r = 1, 2, \dots, R; \\
 & b_{jg'o} \geq \sum_{g=1}^G \sum_{n \in g, n \neq o \text{ if } g=g'} \gamma_{gn} b_{jgn}, j = 1, 2, \dots, J; \\
 & \sum_{n \in (g=1), n \neq o \text{ if } g=g'} \gamma_{gn} = \phi_1, \sum_{n \in (g=2), n \neq o \text{ if } g=g'} \gamma_{gn} = \phi_2, \dots, \sum_{n \in (g=G), n \neq o \text{ if } g=g'} \gamma_{gn} \\
 & \quad = \phi_g; \\
 & \left. \sum_{g=1}^G \phi_g = 1; \phi_g = 1 \text{ or } 0; \gamma_{gn} \geq 0; n \in g, n \neq o \text{ if } g = g' \right\}
 \end{aligned} \tag{16}$$

where  $P^{nc-meta} = \{P^1 \cup P^2 \cup \dots \cup P^G\}$ , and  $\gamma_{gn}$  is a weighting vector of the  $n$ th DMU in group  $g$  with reference to the non-convex metafrontier. We can now discuss the super-efficiency issue under the assumption that the DMU( $x_0, y_0, b_0$ ) is MSBM-efficient and defines the non-convex metafrontier eco-efficiency. Unlike the standard slacks-based measure (SBM) model, the MSBM model is a range-adjusted measure. The optimal objective value for the  $o$ th DMU in group  $g'$  ( $o = 1, 2, \dots, N_{g'}; g' = 1, 2, \dots, G$ ) with reference to the non-convex metafrontier is estimated as:

$$\begin{aligned}
 \rho_{g'o}^* = \min & \frac{1 + \frac{1}{M} \sum_{m=1}^M \frac{s_{mg'o}^x}{\Delta_{mg'o}}}{1 - \frac{1}{R+J} \left( \sum_{r=1}^R \frac{s_{rg'o}^y}{\Delta_{rg'o}} + \sum_{j=1}^J \frac{s_{jg'o}^b}{\Delta_{jg'o}} \right)} \\
 \text{s.t. } & x_{mg'o} - \sum_{g=1}^G \sum_{n \in g, n \neq o \text{ if } g=g'} \gamma_{gn} x_{mgn} + s_{mg'o}^x \geq 0, m = 1, 2, \dots, M; \\
 & \sum_{g=1}^G \sum_{n \in g, n \neq o \text{ if } g=g'} \gamma_{gn} y_{rgn} - y_{rg'o} + s_{rg'o}^y \geq 0, r = 1, 2, \dots, R; \\
 & b_{jg'o} - \sum_{g=1}^G \sum_{n \in g, n \neq o \text{ if } g=g'} \gamma_{gn} b_{jgn} + s_{jg'o}^b \geq 0, j = 1, 2, \dots, J; \\
 & 1 - \frac{1}{R+J} \left( \sum_{r=1}^R \frac{s_{rg'o}^y}{\Delta_{rg'o}} + \sum_{j=1}^J \frac{s_{jg'o}^b}{\Delta_{jg'o}} \right) \geq \varepsilon; \\
 & \sum_{n \in (g'=1), n \neq o \text{ if } g=g'} \gamma_{gn} = \phi_1, \quad \sum_{n \in (g'=2), n \neq o \text{ if } g=g'} \gamma_{gn} = \phi_2, \dots, \\
 & \sum_{n \in (g'=G), n \neq o \text{ if } g=g'} \gamma_{gn} = \phi_G; \\
 & \sum_{g=1}^G \phi_g = 1; \phi_g = 1 \text{ or } 0; s^x, s^y, s^b, \gamma \geq 0; \\
 & \Delta_{mg'o} = x_{mg'o} - \min(x_{mg'}); \\
 & \Delta_{rg'o} = \max(y_{rg'}) - y_{rg'o}; \\
 & \Delta_{jg'o} = b_{jg'o} - \min(b_{jg'})
 \end{aligned} \tag{17}$$

where the DMU under evaluation is denoted as DMU $_{g'o}$ ,  $\gamma$  in Model (17) are non-negative weights, and  $s_{mko}^x$ ,  $s_{rko}^y$ , and  $s_{jko}^b$  represent input slacks, desirable output slacks, and undesirable output slacks, respectively. The term  $\varepsilon$  is a non-Archimedean value, and this constraint ensures a positive denominator in the objective function.  $\phi_g$  represents the subset constraints of the input-output combinations for the  $g$ th group frontier. The super-efficiency model is different from the standard one, as the term DMU $_{g'o}$  is excluded from the reference set (Andersen and Petersen 1993), reflected by  $n \neq o$ . Our measures of eco-efficiency are derived from the optimal solutions of Model (17).

### 3.2 Econometric Specification

We use the spatial Durbin model with a two-regime framework as in Elhorst and Fréret (2009), with the added component of political competition given that we are investigating its impact on eco-efficiency. This kind of econometric specification includes the spatial lags of all the independent variables in addition to the spatial lag of the dependent variable with two regimes:

$$EE_{it} = \alpha + \rho_1 d_{it} \sum_{j=1}^N w_{jt} EE_{jt} + \rho_2 (1 - d_{it}) \sum_{j=1}^N w_{jt} EE_{jt} + \beta X_{it} + \sum_{j=1}^N w_{jt} X_{jt} \theta + \mu_i + \lambda_t + u_{it} \quad (18)$$

$$d_{it} = \begin{cases} 1, & \text{if } EE_{it} > \sum_{j=1}^N w_{ijt} EE_{jt}, i \neq j \\ 0, & \text{otherwise} \end{cases} \quad (19)$$

where  $EE_{it}$  denotes eco-efficiency of city  $i$  at period  $t$ ;  $N$  is the number of spatial units;  $w_{ij}$  is an element of a spatial weight matrix  $W$  that describes the spatial arrangement of the cities in the sample; and  $\sum_{j=1}^N w_{jt} X_{jt} \theta$  is the spatial Durbin term. The binary variable  $d_{it}$  takes a value of 1 if city  $i$ 's eco-efficiency level is higher than the weighted average of its neighbors, and 0 otherwise. Based on its set-up, it should be clear that  $\rho_1$  and  $\rho_2$  are the peer-effect coefficients.  $\rho_1$  measures how a city's eco-efficiency might be affected by its neighboring regions with inferior environmental performance on average, while  $\rho_2$  is applicable in the scenario when the city is outperformed by its neighbors. The magnitude and the signs of  $\rho_1$  and  $\rho_2$  are important because they help us to determine changes in eco-efficiency levels (increase or decrease), as well as the pattern of the directional relationship between eco-efficiency trends (convergence or divergence). Finally,  $X_{it}$  represents a vector of control variables that affect eco-efficiency, with associated parameters in vector  $\beta$ . In selecting the factors of eco-efficiency, we turn to the existing literature for wisdom. The renowned IPAT identity links anthropogenic impacts in environment ( $I$ ) to three key driving forces – population size ( $P$ ), affluence ( $A$ ), and technology ( $T$ ) – through a multiplicative function, i.e.,  $I = PAT$  (Ehrlich and Holdren 1972; Fischer-Kowalski and Amann 2001; Ehrenfeld 2005). For our study, we adopt the framework of the STIRPAT model, a stochastic form of IPAT identity proposed by Dietz and Rosa (1997), and choose the following factors as control variables in  $X_{it}$ :

- Economic development (*pgdp*), wage level of employees (*wage*), and population agglomeration (*popd*). In this study, economic development is proxied by per capita GDP, population density is the demographic measurement, and average salary is used to represent the affluence of urban residents.
- Foreign direct investment (*sfdi*). FDI enhances the production efficiency of domestic enterprises via a technology spillover effect (Javorcik 2004), and is naturally an important agent in urban economic development. Based on data availability, we utilize the actual use of FDI as an indicator in this study.
- Industrial structure (*sind*). Following York et al. (2003), the percentage of GDP contributed by the secondary (industry) sector is used as the key indicator to reflect the economic structure of each city.



- d) Technology and innovation (*inno*). Jin et al. (2019) have found that technology and innovation have greater beneficial impacts on coastal cities than on inland cities in the PRC. In our study, we use city innovation to represent technological change, with a relevant indicator from Kou and Liu (2017).
- e) Environmental regulation (*er*). Based on data availability, environmental regulation is proxied by an indicator that aggregates the removal rate of SO<sub>2</sub>, the treatment rate of domestic sewage, and the comprehensive utilization ratio of solid waste.

Commonly used in spatial econometrics, the spatial weights matrix **W** models spatial interdependence among observations (LeSage and Pace 2009), or, specific to our study, it describes the exogenous pattern of how neighboring cities are spatially inter-connected to each other. In the spatial econometrics literature, weight matrices are conventionally constructed based on geographic proximity, such as contiguity and geographic distance; however, estimation results are not sensitive to the specifications of spatial weights matrices, according to LeSage and Pace (2014). In this study, we specify two different spatial weights matrices, the first being defined as follows:<sup>7</sup>

$$w_{ij} = \begin{cases} 1, & \text{if cities } i \text{ and } j \text{ belong to the same province} \\ 0, & \text{otherwise} \end{cases} \quad (20)$$

Elements on the main diagonal of the matrix are set to zero by convention. There is one special note regarding the four municipalities: Beijing, Tianjin, Shanghai, and Chongqing. They are under the direct administration of the central government, so in reality they each have the same rank as provinces within the Chinese political hierarchical structure. However, for the purpose of our study they are set at the same level as other cities, i.e., these four municipalities would compete among themselves politically in the same sense that there are no other municipality cities from the same province.

Next, we introduce the probability of political promotion, with the revised spatial weights matrix defined as follows:

$$\tilde{w}_{ij} = \begin{cases} \bar{c}_i \times w_{ij}, & \text{if cities } i \text{ and } j \text{ belong to the same province} \\ 0, & \text{otherwise} \end{cases} \quad (21)$$

where  $\bar{c}_i$  represents the average political intensity during the study period, and is measured as below in Equation (22), following Liu et al. (2012):

$$\bar{c}_i = \frac{1}{T} \sum_{t=1}^T \left( \frac{\sum_{i=1}^Q \delta_{it} - \delta_{it}}{2Q} \right) \quad (22)$$

where  $Q$  is the number of cities within the same province,  $T$  is the duration of the period, and  $\delta_{it}$  denotes the number of Party secretary turnovers of city  $i$  in period  $t$ . To re-estimate Equation (18), it is also necessary that we revise the definition of the binary variable  $d_{it}$  accordingly, as follows:

$$\tilde{d}_{it} = \begin{cases} 1, & \text{if } EE_{it} > \sum_{j=1}^N \tilde{w}_{ijt} EE_{jt}, i \neq j \\ 0, & \text{otherwise} \end{cases} \quad (23)$$

<sup>7</sup> To normalize the outside influence upon each city, the weights matrix is subject to standardization, so that elements in the same row sum up to one.

### 3.3 Data

In this study we examine 191 cities at prefecture level and above in the PRC during the period 2003–2015. Our sample does not include any of the following due to data unavailability: Hong Kong, China; Macau, China; Taipei, China; and Tibet Autonomous Region. The input and output data are introduced as follows.

- (1) Desirable output. We use data on real GDP, measured at constant 2010 prices, wherever applicable throughout this paper.
- (2) Undesirable output. We employ the entropy weight method to generate a composite environmental pollution index (EPI) of four pollutants: carbon dioxide emissions; industrial wastewater discharge; sulfur dioxide emissions; and industrial soot-dust emissions. We use Huang et al.'s (2018) approach to estimate carbon dioxide emissions, while the other three pollutants' data are collected from the *China City Statistical Yearbooks (CCSY)*, 2004–2016.
- (3) Labor force. We use the size of the employed population as a proxy in our study, based on data availability.
- (4) Capital stock. We adopt the perpetual inventory method by Ke and Xiang (2012) to estimate capital stock –  $K_{i,t} = I_{i,t} + (1 - \sigma_{i,t})K_{i,t-1}$  – where the total capital stock of city  $i$  at time  $t$ ,  $K_{i,t}$ , is the sum of fixed assets accumulated from the past year ( $\sigma_{i,t}$  is the depreciation rate) and new physical capital investment,  $I_{i,t}$ .
- (5) Land usage. We use the construction land area as the proxy based on data accessibility.
- (6) Energy consumption. Information on primary energy consumption in 2003–2013 is directly extracted from Huang et al. (2018), and we also use their method to estimate for the data for the two years of 2014 and 2015. Primary energy consumption is converted to standard coal equivalent (SCE), the standard unit in Chinese energy statistics.

**Table 1: Descriptive Statistics**

	Unit	Obs.	Mean	Std. Dev.	Min.	Max.
<i>Panel A: Input and output variables for DEA</i>						
Labor	10 <sup>4</sup> persons	2,483	56.51	79.65	5.49	986.87
Capital	10 <sup>8</sup> CNY	2,483	1,340.00	1,990.00	27.50	22,000.00
Land	km <sup>2</sup>	2,483	14,908.09	12,618.12	1,565.00	90,659.00
Energy	Tons of SCE	2,483	1,573.91	1,572.05	53.79	11,719.50
GDP	10 <sup>8</sup> RMB	2,483	1,730.00	2,410.00	50.15	25,000.00
EPI	–	2,483	4.03	3.70	0.07	56.19
<i>Panel B: Variables used in econometric model</i>						
<i>ee</i>	–	2,483	0.47	0.20	0.20	1.16
<i>pgdp</i>	CNY/person	2,483	3.76	4.31	0.30	42.25
<i>wage</i>	–	2,483	10.20	0.55	5.93	11.64
<i>popd</i>	10 <sup>4</sup> persons/km <sup>2</sup>	2,483	0.05	0.04	<0.01	0.27
<i>sfdi</i>	–	2,483	0.13	0.20	0.00	1.44
<i>sind</i>	–	2,483	0.49	0.11	0.15	0.91
<i>inno</i>	–	2,483	0.08	0.39	0.00	8.49
<i>er</i>	–	2,483	0.40	0.18	0.03	0.79

Note: CNY denotes Chinese Yuan.

The descriptive statistics and correlation coefficients of the dependent and control variables are displayed in Tables 1 and 2, respectively. Definitions of each variable and data source are provided in Appendix B. Given that the correlation coefficients among the independent variables are small, the possibility of multicollinearity is dismissed.

**Table 2: Correlation Coefficients among Dependent and Control Variables**

Variable	<i>ee</i>	<i>pgdp</i>	<i>wage</i>	<i>popd</i>	<i>sfdi</i>	<i>sind</i>	<i>inno</i>
<i>pgdp</i>	0.28***	1					
<i>wage</i>	−0.01	0.54***	1				
<i>popd</i>	0.38***	0.31***	0.16***	1			
<i>sfdi</i>	0.24***	0.55***	0.27***	0.45***	1		
<i>sind</i>	−0.02	0.20***	0.17***	0.11***	0.12***	1	
<i>inno</i>	0.16***	0.50***	0.30***	0.30***	0.24***	−0.14***	1
<i>er</i>	−0.04**	0.36***	0.65***	0.19***	0.22***	0.18***	0.18***

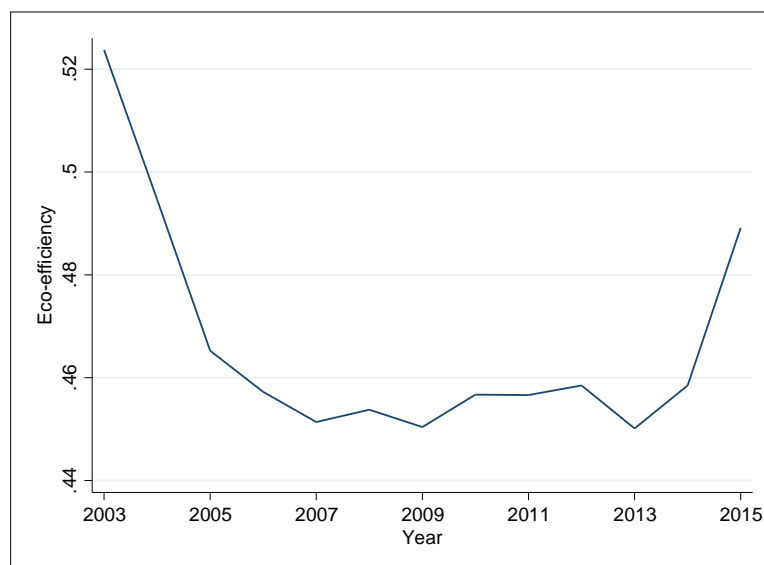
Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## 4. RESULTS AND DISCUSSION

### 4.1 Eco-efficiency: The National Trend

We first check the national average of eco-efficiency (illustrated in Figure 3) and see how it has evolved over the years. The U-shaped pattern is immediately apparent. In particular, the eco-efficiency level declined in the earliest years of our study period; this adverse trend seemed to be halted in 2007, as the eco-efficiency level remained largely flat until around 2013, and then rose quite rapidly ever since.

**Figure 3: The Trend of Eco-efficiency in the PRC: 2003–2015**



This phenomenon coincides with a critical period of change in environmental protection and policy making in the PRC. In 2010, the binding targets set for the National 11th Five-Year Plan (2005–2010) were largely met, with great strides made in terms of both energy conservation and emissions reduction. Environmental quality has improved significantly:

for example, the average sulfur dioxide concentrations in KEP cities have decreased by 26.3% compared to 2005. Encouraged by this success, the National 12th Five-Year Plan (2011–2015) set the ambitious goal of further reducing the total emissions of all major pollutants by 8% to 10%, and expanded the list of pollution indicators. Environmental protection was thus made a priority. According to the National 12th Five-Year Plan for Environmental Protection published by the State Council of China in 2011, for the first time ever local environmental quality was made an important consideration in the annual evaluations of government officials at all levels, and environmental protection was given the power of veto in this process. Such unprecedented change provides evidence of the central government's will and determination. Moreover, given that it has been integrated into the political assessment of local officials, it has quickly started to take effect, as corroborated by the remarkable turnaround in the nationwide trend of eco-efficiency.

## 4.2 Eco-efficiency: Heterogeneities across Groups

Understandably, eco-efficiency can vary quite drastically across different regions due to factors such as heterogeneity in resource endowment, geographic condition, and environmental policies. Next, we present four different criteria, each of which would help to categorize our sample of 191 Chinese cities into two mutually exclusive groups.

In the PRC, cities in the eastern (or coastal) regions are generally at a more advanced level of economic growth, whereas their counterparts in the central and western (or inland) regions tend to perform worse economically. Using the first criterion, we divide all cities into two groups: eastern vs. central/western. In our sample, there are 71 cities in the eastern group.

Different cities may exhibit different patterns of natural resource endowment and industrial structure, which in turn may have an impact on environmental quality. Based on the definition and list of resource-based (RB) cities in *Planning for Sustainable Development of Resource-based Cities in China (2013-2020)*, a document issued by the State Council of China in 2013, we can divide all of the cities into two groups: RB vs. non-RB. Our sample has 78 RB cities.

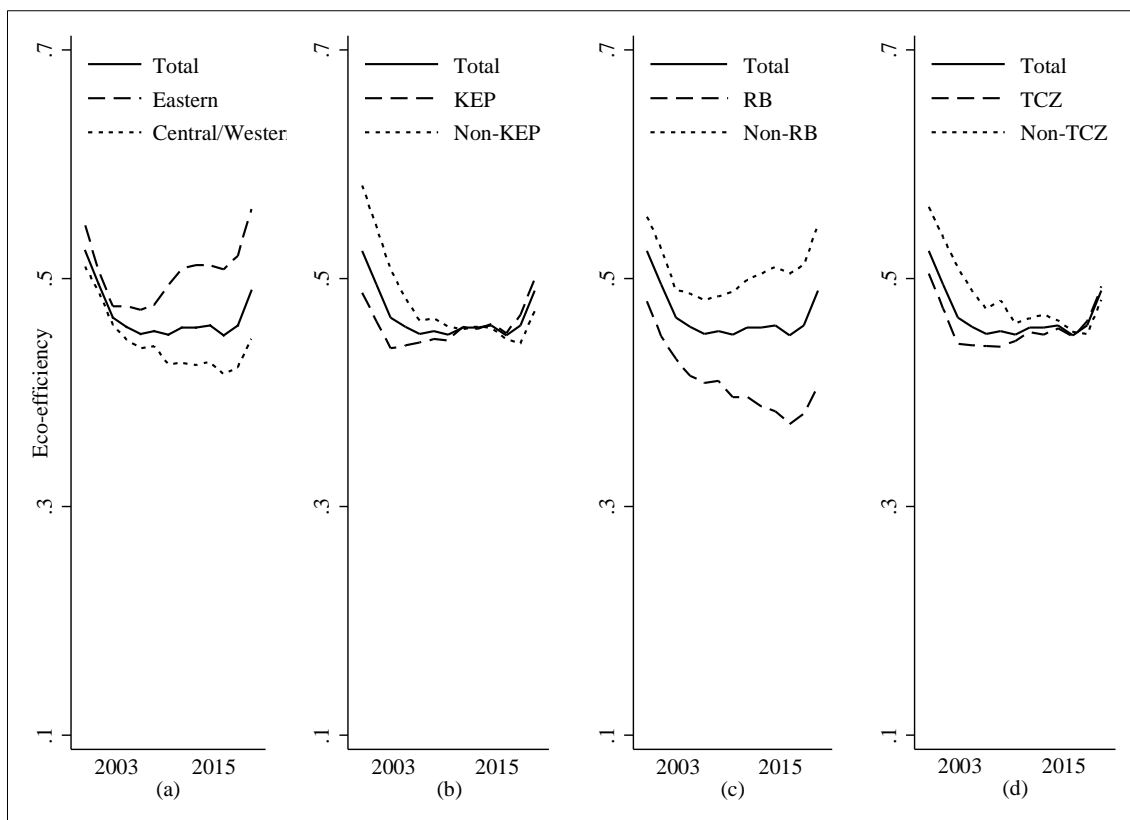
More than 100 cities in the PRC have been designated as KEP cities. They are usually cities of considerable political and/or economic importance, such as municipalities, provincial capital cities, open coastal cities, and major tourist cities, although the list also includes cities with historical environmental issues and a more pressing need for environmental protection. KEP cities are subject to more stringent environmental policies and standards compared to non-KEP ones. The list of 117 KEP cities in our study is compiled based on the *China Environmental Yearbook, 2012–2016*.

According to the Law on the Prevention and Control of Atmospheric Pollution, areas with existing or potential acid rain or severe sulfur dioxide pollution may be designated as acid rain control zones or sulfur dioxide control zones, often collectively referred to as TCZ cities. Our sample contains 127 TCZ cities, and, similar to the KEP cities, they are subject to more stringent environmental policies and standards.

Figure 4 illustrates the heterogeneities across groups. Figure 4a suggests that the gap between eastern and central/western cities seems to have widened over time. Similarly, in Figure 4c one can see that RB cities have always had significantly lower eco-efficiency levels than non-RB cities. Another concerning observation is that both RB cities and cities in the central/western regions witnessed a continual decline in eco-efficiency until around 2013, when the trend was reserved. This similarity might be explained by the fact that most RB cities are located in central/western regions with

a historically unfavorable industrial structure, weaker economic foundation, less advanced technology, and more severe environmental issues.

**Figure 4: Eco-efficiency Trends: Heterogeneities across Groups**



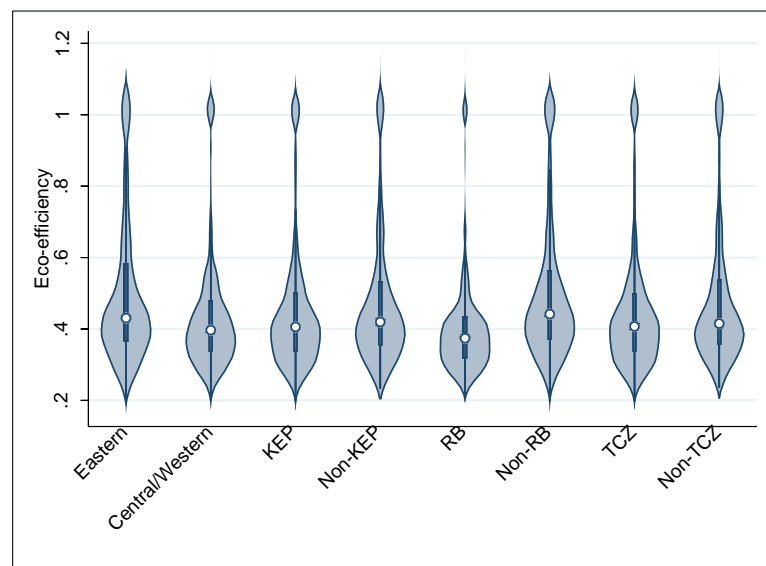
According to Figure 4b, although KEP cities started with inferior records in eco-efficiency compared to their non-KEP counterparts, the gap gradually narrowed, until around 2012 when they overtook them. Considering that the group of KEP cities are a mixture of cities with historically poor environmental records and cities of political importance, this overall pattern of catching up and then overtaking makes sense. As can be seen in Figure 4d, the dynamic evolution of eco-efficiency in TCZ vs. non-TCZ looks very similar to the aforementioned KEP vs. non-KEP comparison.

In addition to the above graphical evidence, we can further investigate the inter-group disparity in eco-efficiency with a violin plot and a mean test. In Table 3, we compare the means of eco-efficiency between each pair of groups. We can see that, on average, cities in the eastern region have superior eco-efficiency to those in the central/western regions; similarly, non-KEP, non-RB, and non-TCZ cities outperform their KEP, RB, and TCZ counterparts, respectively. Although the respective gaps vary between 0.02 and 0.10, the disparity in eco-efficiency between each pair of groups is statistically significant at the 1% level. The violin plot in Figure 5 largely confirms the patterns of the relationships between each pair, including that the median value of the non-TCZ cities' eco-efficiency is higher than that of the TCZ cities, albeit only slightly.

**Table 3: Mean Test of Eco-efficiency**

Statistics	Eastern	KEP	RB	TCZ
Mean	0.5050	0.4585	0.4088	0.4578
Max.	1.0924	1.0919	1.1632	1.0924
Min.	0.1984	0.1984	0.2136	0.1984
Std.Dev.	0.2094	0.1898	0.1551	0.1882
	Central/Western	Non-KEP	Non-RB	Non-TCZ
Mean	0.4440	0.4795	0.5065	0.4841
Max.	1.1632	1.1632	1.0924	1.1632
Min.	0.1985	0.2330	0.1984	0.2360
Std.Dev.	0.1770	0.1946	0.2043	0.1979
T-TEST	0.0610***	-0.0210***	-0.0977***	-0.0263***

Note: \*\*\*  $p < 0.01$ .

**Figure 5: Distributions of Eco-efficiency for Different Cities**  
(Color figure online)

### 4.3 Baseline Results

We present the estimation results of Equation (18) in Table 4, with a particular interest in examining how a city's eco-efficiency is affected by the performance of its neighbors. The case without the consideration of political competition is shown in the first column, and the case with in the second. Our estimates of  $\rho_1$  and  $\rho_2$  depict an interesting pattern of dynamics. It seems that a city may be incentivized to emulate its outstanding neighbors after witnessing their excellence, resulting in improved eco-efficiency. On the other hand, outperforming its neighbors seems to serve as a disincentivizing factor for the leader, perhaps due to complacency, leading to diminished eco-efficiency. Based on our findings, we can call  $\rho_1$  the "incentivizing effect coefficient," and  $\rho_2$  the "disincentivizing effect coefficient." This finding is important because it reveals a pattern of convergence among different regions with different levels of eco-efficiency.

It can also be noted that the positive, incentivizing effect appears to be stronger than the negative, disincentivizing effect. According to Table 4, without consideration of political competition, a city would see its eco-efficiency decrease by 0.240% triggered by a 1% increase in its lower performing neighbors, but an increase by 0.775% with a 1% increase in its higher performing neighbors. This results in a positive net peer effect, reinforcing the upward trend of eco-efficiency in addition to the pattern of convergence. All results are statistically significant at the 1% level. Moreover, among the seven control variables, we find that economic development (*pgdp*), average salary (*wage*), population agglomeration (*popd*), and technology spillover of innovation (*inno*) have positive effects on eco-efficiency, while industrial structure (*sind*) has negative effects. It also seems that *popd* exerts the greatest positive impact on eco-efficiency out of all the control variables.

**Table 4: Baseline Estimates of Political Competition on Eco-efficiency (2003–2015)**

Variable	Without Political Competition	With Political Competition
	$d$	$\tilde{d}$
$\rho_1$	−0.2404*** (−5.6749)	−0.2376*** (−5.6174)
$\rho_2$	0.7746*** (17.4174)	0.6756*** (15.1150)
<i>pgdp</i>	0.0109*** (6.5396)	0.0112*** (6.6504)
<i>wage</i>	0.0806*** (5.1131)	0.0742*** (4.6578)
<i>popd</i>	0.7503** (2.2685)	0.7034** (2.1057)
<i>sfdi</i>	0.0190 (0.5232)	0.0289 (0.7939)
<i>sind</i>	−0.0835 (−1.5109)	−0.0973* (−1.7447)
<i>inno</i>	0.0278*** (3.3584)	0.0286*** (3.4058)
<i>er</i>	0.0091 (0.5334)	0.0125 (0.7264)
Observations	2,483	2,483
R-squared	0.8548	0.8506
Log-likelihood	2,897.7201	2,881.6590

Notes: t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. The definition of each variable can be found in Appendix B. Spatial lags of the control variables are not presented in order to save space. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

#### 4.4 Effects of Political Competition: Sub-sample Estimations

We now turn our attention to the effects of political competition on eco-efficiency. Revisiting Table 4, we can see that when political competition is taken into consideration, both disincentivizing and incentivizing effects decline in magnitude in terms of absolute value, as can also be seen in Table 4. If a city currently outperforms its competitors, its eco-efficiency is induced to drop, but at a lower rate of 0.238%; however, if it currently has an inferior eco-efficiency level than its competitors on average, this (positive) peer pressure effect is reported as a 0.676% increase. Either way, it seems that the convergence is slowed down; moreover, the net peer effect remains positive, yet it is reduced in magnitude compared to the scenario without consideration of political

competition. We further investigate these effects for different periods in our study. Based on the estimation results summarized in Table 5, we can see that political competition amplified the peer effects (both disincentivizing and incentivizing effects) during the 2003–2010 period, but attenuated them during the 2011–2015 period, as well as across the period as a whole.

**Table 5: Impacts of Political Competition on Eco-efficiency: Different Periods**

Variable	2003–2010		2011–2015	
	$d$	$\bar{d}$	$d$	$\bar{d}$
$\rho_1$	−0.3474*** (−5.6191)	−0.4145*** (−6.7515)	−0.4334*** (−5.6862)	−0.3818*** (−4.9151)
$\rho_2$	0.6937*** (10.3821)	0.6940*** (10.2894)	0.8854*** (9.1345)	0.6759*** (8.5961)
$pgdp$	0.0160*** (5.6573)	0.0155*** (5.4644)	0.0139*** (3.5823)	0.0145*** (3.7084)
$wage$	0.0785*** (4.4271)	0.0729*** (4.0816)	0.0220 (0.6953)	0.0380 (1.1940)
$popd$	0.5119 (1.4076)	0.4198 (1.1489)	1.4145 (1.5062)	1.4482 (1.5260)
$sfdi$	−0.0588 (−1.1446)	−0.0555 (−1.0786)	−0.0511 (−0.7576)	−0.0267 (−0.3959)
$sind$	−0.1496* (−1.8875)	−0.1325* (−1.6668)	0.0780 (0.7160)	0.0891 (0.8117)
$inno$	−0.0197 (−0.5428)	0.0379 (1.0389)	−0.0009 (−0.0696)	0.0074 (0.5382)
$er$	0.0035 (0.1446)	−0.0002 (−0.0101)	0.0293 (1.1836)	0.0364 (1.4556)
Observations	1,528	1,528	955	955
R-squared	0.8810	0.8791	0.9163	0.9139
Log-likelihood	1,902.8498	1,900.0051	1,450.7196	1,448.4074

Notes: t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. The definition of each variable can be found in Appendix B. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

We now take a closer look at peer effects across different regions and periods, with the estimation results summarized in Table 6. We can see that all estimated values of  $\rho_1$  with statistical significance are negative, and that all estimated values of  $\rho_2$  are positive. This is true both with and without the consideration of political competition, indicating an unambiguous pattern of convergence in eco-efficiency, in line with our theoretical projection.

In the following step, we examine the effects of political competition on the pattern of convergence by calculating and analyzing  $\rho_2 - \rho_1$  based on information from Table 6. Keep in mind that  $\rho_1$  and  $\rho_2$  both contribute to convergence, although they work in opposite directions. Furthermore, given that  $\rho_1 < 0$  and  $\rho_2 > 0$ , we know that  $\rho_2 - \rho_1$  is the same as  $|\rho_1| + |\rho_2|$ . We use this term to loosely measure the rate (or degree) of convergence, and use Figure 6 (a, b, c) to illustrate our findings. Note that the values estimated without political competition are marked by circles, while diamonds represent values with.

First, it is easy to reaffirm the pattern of convergence, as all values appear on the right side of the zero value. Next, regarding the effect of political competition, we can see that

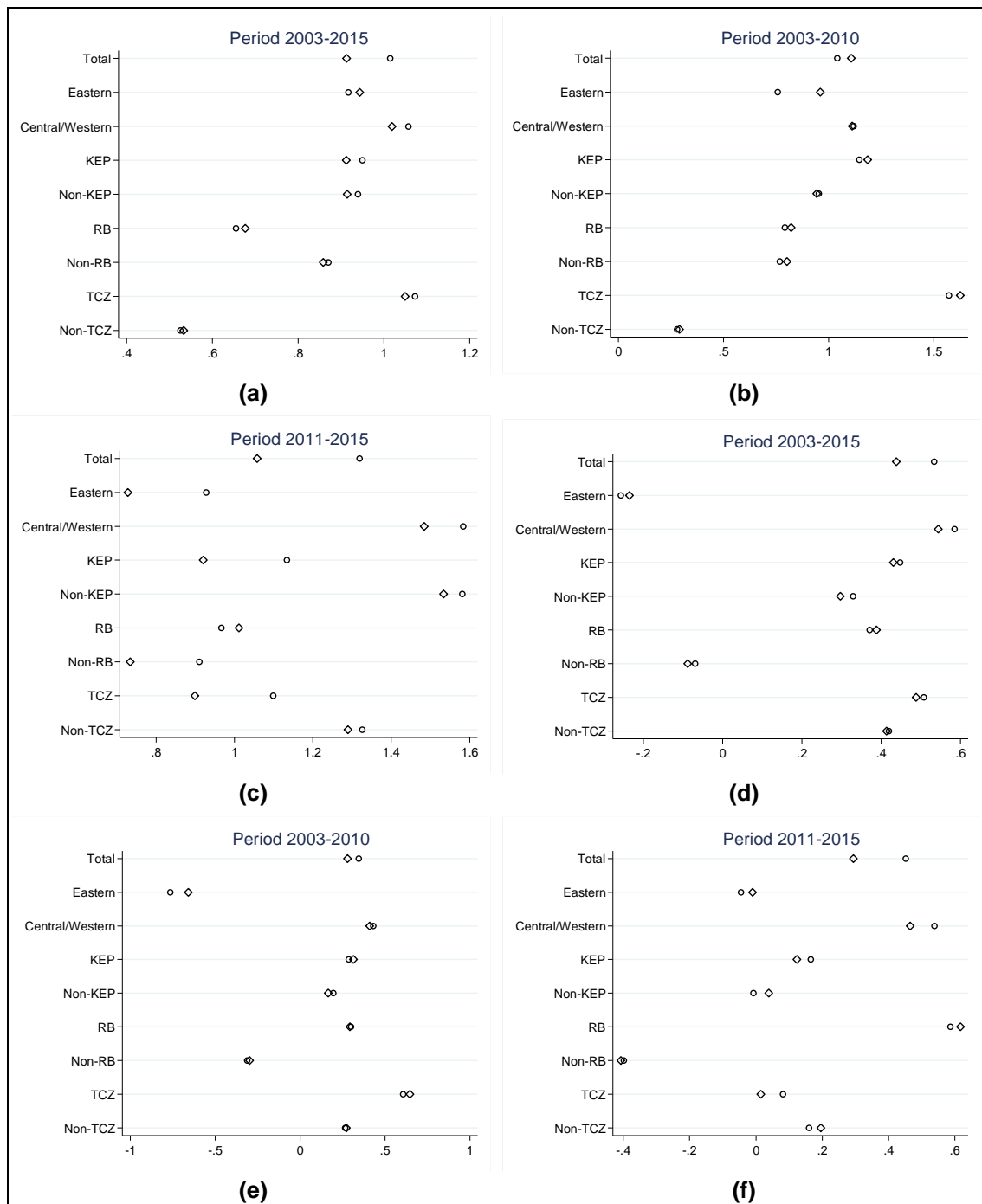


it reduces the speed of convergence, based on the full sample during the entire period 2003–2015. When we break the sample down to different groups and different periods, the experiences vary. Particularly striking is the stark difference before and after 2010, a critical time of transition in the PRC when the 11th Five-Year Plan was completed and the 12th Five-Year Plan was about to commence. The most recent period witnessed much more significant (slowing) effects of political competition on the convergence of eco-efficiency, as illustrated.

Although it would be intriguing to explore the spatial, temporal, and spatiotemporal heterogeneities in the convergence pattern, in our opinion an even more meaningful task is to identify the direction of the trend in eco-efficiency, as well as how it is affected by political competition. As previously mentioned,  $\rho_1$  and  $\rho_2$  work in opposite directions, and the former can perhaps be labeled as the negative peer effect out of the two. We calculate and analyze  $\rho_1 + \rho_2$ , and use this term to loosely measure the “net” peer effect for a city: it should be obvious that both its sign and its magnitude would disclose important information about the trend of eco-efficiency for any region. Based on Figure 6 (d, e, f), we find that the net peer effect is positive for the full sample and for most groups in general, which is encouraging because it indicates an upward trend of eco-efficiency. The only two exceptions on the chart are eastern and non-RB groups, both of which seem to receive negative net peer effects over time. This should not come as a complete surprise, however, as their opposite groups (central/western, and RB cities, respectively) have struggled historically and are responsible for inflicting a large  $\rho_1$  in terms of absolute value. This largely reaffirms the information in Figure 4, which displays the heterogeneous patterns of the trend in eco-efficiency across groups, and shows that only in very recent years have the trends started to turn upward in central/western regions and for RB cities. It is also interesting to note that the negative net peer effect has almost vanished for the eastern group in the most recent period, while the same cannot yet be said about the non-RB cities. This may be linked to the timing of different policies, as China Western Development<sup>8</sup> was officially launched about two decades ago, long before the central government’s initiatives targeting resource-based cities (2013), so it may be natural to expect a later turning point. Lastly, it seems that political competition has an adverse impact on eco-efficiency for the full sample and for most groups, as suggested by Figure 4 (d, e, f). Again, this finding confirms our theoretical model’s projection.

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<sup>8</sup> In late 1999, after two decades of pursuing coastal development, the PRC’s leaders announced a change in the PRC’s regional development strategy and initiated the western drive. Starting from 2001 the PRC government has offered preferential policies to the western region in terms of capital input, investment environment, internal and external opening-up, development of science and education, and human resources.

**Figure 6: The Effects of Political Competition on Eco-efficiency**

## 4.5 Robustness Check

To check the robustness of our results, we adopt an alternative measure of eco-efficiency – the Meta-US-SBM model proposed by Huang et al. (2018) – to see how the coefficient estimates in the baseline regression may behave. The Meta-US-SBM model simultaneously incorporates metafrontier, undesirable output, and super-efficiency into a slacks-based measure (Tone 2001), and its strengths lie in its efficient comparison of the same DMU in different years due to technological progress, as well as its

identification of DMUs located on the efficient frontier for considering super-efficiency. The new regression generates no major change in the results, indicating that our main findings are robust. The new set of estimation results are presented in Appendix C for the purpose of saving space.

**Table 6: Estimation Results of Sub-samples at Different Periods**

		Eastern		Central/Western		KEP		Non-KEP	
		$d$	$\tilde{d}$	$d$	$\tilde{d}$	$d$	$\tilde{d}$	$d$	$\tilde{d}$
2003–2015	$\rho_1$	−0.5870*** (−5.8525)	−0.5894*** (−6.0344)	−0.2362*** (−4.5447)	−0.2375*** (−4.4928)	−0.2511*** (−5.4088)	−0.2407*** (−5.1671)	−0.3052*** (−4.0535)	−0.3086*** (−4.0496)
	$\rho_2$	0.3302*** (3.8962)	0.3547*** (4.0491)	0.8213*** (13.8975)	0.7818*** (13.2364)	0.6990*** (14.7796)	0.6718*** (14.6059)	0.6346*** (11.6215)	0.6063*** (10.8427)
2003–2010	$\rho_1$	−0.7607*** (−4.6806)	−0.8090*** (−5.2195)	−0.3437*** (−4.7367)	−0.3508*** (−4.7877)	−0.4297*** (−6.3680)	−0.4360*** (−6.5150)	−0.3786*** (−3.6703)	−0.3884*** (−3.6892)
	$\rho_2$	−0.0028 (−0.0187)	0.1513 (0.9469)	0.7754*** (9.1725)	0.7612*** (9.1517)	0.7164*** (10.0129)	0.7505*** (10.5090)	0.5750*** (7.3323)	0.5550*** (7.0480)
2011–2015	$\rho_1$	−0.4863*** (−3.1425)	−0.3689** (−2.5292)	−0.5228*** (−5.5975)	−0.5096*** (−5.2609)	−0.4841*** (−5.4242)	−0.3985*** (−4.4300)	−0.7945*** (−5.0447)	−0.7476*** (−4.8923)
	$\rho_2$	0.4412*** (3.5798)	0.3584*** (2.8359)	1.0610*** (10.8509)	0.9746*** (9.5713)	0.6497*** (7.6882)	0.5217*** (6.2234)	0.7866*** (12.4526)	0.7860*** (12.4599)
		RB		Non-RB		TCZ		Non-TCZ	
		$d$	$\tilde{d}$	$d$	$\tilde{d}$	$d$	$\tilde{d}$	$d$	$\tilde{d}$
2003–2015	$\rho_1$	−0.1422** (−2.4412)	−0.1444** (−2.5053)	−0.4700*** (−7.5715)	−0.4732*** (−7.6169)	−0.2823*** (−5.9947)	−0.2808*** (−5.9355)	−0.0531 (−0.8520)	−0.0597 (−0.9532)
	$\rho_2$	0.5134*** (12.8331)	0.5329*** (13.4887)	0.4008*** (8.7949)	0.3858*** (8.3367)	0.7903*** (20.8294)	0.7693*** (19.1219)	0.4728*** (11.2262)	0.4736*** (11.2895)
2003–2010	$\rho_1$	−0.2455*** (−2.9761)	−0.2642*** (−3.1662)	−0.5395*** (−6.1881)	−0.5499*** (−6.3499)	−0.4833*** (−7.9945)	−0.4893*** (−8.1285)	−0.0073 (−0.0910)	−0.0094 (−0.1176)
	$\rho_2$	0.5464*** (10.5832)	0.5576*** (10.9807)	0.2283*** (3.1311)	0.2527*** (3.4664)	1.0899*** (30.5949)	1.1365*** (24.3467)	0.2731*** (3.9849)	0.2812*** (4.1590)
2011–2015	$\rho_1$	−0.1900** (−2.0422)	−0.1973** (−2.1635)	−0.6542*** (−5.4939)	−0.5709*** (−4.9006)	−0.5084*** (−5.2750)	−0.4420*** (−4.5728)	−0.5830*** (−4.2768)	−0.5469*** (−4.1320)
	$\rho_2$	0.7763*** (19.4108)	0.8138*** (21.9443)	0.2560*** (3.0390)	0.1631* (1.8587)	0.5900*** (7.1936)	0.4564*** (5.0633)	0.7428*** (20.2935)	0.7428*** (20.4372)

Notes: The t- statistics are given in parentheses. All regressions include control variables, spatial- and time period-fixed effects. The definition of each control variable can be found in Appendix B. More details can be found in Appendix D (heterogeneity across cities for the period 2003–2015), Appendix E (heterogeneity across cities for the period 2003–2010) and Appendix F (heterogeneity across cities for the period 2011–2015). \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

## 5. CONCLUSIONS

Strategic interaction across regions in environmental issues has motivated us to investigate the association of eco-efficiency with peer effects and political competition from both theoretical and empirical perspectives. Political competition among regional government officials without regard to environmental issues would result in a continual deterioration in eco-efficiency in a race-to-the-bottom fashion, and our theoretical analysis re-confirms that the meaningful inclusion of environmental performance in the annual political assessment of local government officials is critical to ensuring the eventual upward trend of eco-efficiency.

To verify these theoretical applications, we have employed the DEA model to compute the eco-efficiency level for 191 Chinese cities. Overall, eco-efficiency evolved in a U-shape pattern for the years 2003–2015. In particular, we have found that the eco-efficiency level declined in the earliest years of our study period when the promotion of local governors largely depended on economic achievement. This trend was reversed when the National 12th Five-Year Plan for Environmental Protection explicitly mandated

local environmental quality as an important consideration in the annual evaluation of government officials at all levels.

Overall, increased political competition leads to a decline in eco-efficiency, as suggested theoretically and confirmed empirically in our study. Furthermore, despite considerable variations in eco-efficiency levels across cities and regions, we have identified a pattern of convergence arising from two peer effects. However, political competition also tends to slow down the convergence process. These findings suggest that a well-designed evaluation system can be effective in motivating bureaucrats to shift their efforts toward a more environmentally friendly growth path.

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## APPENDIX A

First, we derive the first-order condition (FOC) for region  $i$ , with the following optimization condition:

$$(\alpha + N)q_i - \beta(b_i + 1)r_{ii}y_i = 0.$$

Combined with (8), we have the following expanded conditions, one for each region:

$$(\alpha + N)(\widetilde{q}_1 - r_{11}e_1 - r_{12}e_2 - r_{13}e_3 - \cdots - r_{1N}e_N) - \beta(b_1 + 1)r_{11}y_1 = 0,$$

$$(\alpha + N)(\widetilde{q}_2 - r_{21}e_1 - r_{22}e_2 - r_{23}e_3 - \cdots - r_{2N}e_N) - \beta(b_2 + 1)r_{22}y_2 = 0,$$

$$(\alpha + N)(\widetilde{q}_3 - r_{31}e_1 - r_{32}e_2 - r_{33}e_3 - \cdots - r_{3N}e_N) - \beta(b_3 + 1)r_{33}y_3 = 0,$$

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$$(\alpha + N)(\widetilde{q}_N - r_{N1}e_1 - r_{N2}e_2 - r_{N3}e_3 - \cdots - r_{NN}e_N) - \beta(b_N + 1)r_{NN}y_N = 0.$$

We sum up all the above FOCs and utilize the property  $r_{ii} + \sum_j r_{ji} = 1$  as in (9), and can have the following:

$$(\alpha + N) \sum_i (\widetilde{q}_i - e_i) - \beta \sum_i (b_i + 1)r_{ii}y_i = 0.$$

Assuming structural symmetry among regions, and combining equation (7), we can derive the results as (10):

$$y_i = \frac{(\alpha + N)(m_i + \widetilde{q}_i)}{(b_i + 1)(\alpha + N + \beta r_{ii})}.$$

For results (12), we have:

$$\frac{\partial e e_i}{\partial m_i} = \frac{b_i(\alpha + N)\widetilde{q}_i}{(b_i + 1)m_i^2(\alpha + N + \beta r_{ii})} > 0,$$

$$\frac{\partial e e_i}{\partial b} = -\frac{(\alpha + N)(m_i + \widetilde{q}_i)}{(b_i + 1)^2 m_i(\alpha + N + \beta r_{ii})} < 0,$$

$$\frac{\partial e e_i}{\partial \beta} = \frac{b_i(\alpha + N)(m_i + \widetilde{q}_i)r_{ii}}{(b_i + 1)m_i(\alpha + N + \beta r_{ii})^2} > 0,$$

$$\frac{\partial e e_i}{\partial \widetilde{q}_i} = -\frac{b_i(\alpha + N)}{(b_i + 1)m_i(\alpha + N + \beta r_{ii})} < 0,$$

$$\frac{\partial e e_i}{\partial N} = -\frac{b_i(m_i + \widetilde{q}_i)\beta r_{ii}}{(b_i + 1)m_i(\alpha + N + \beta r_{ii})^2} < 0.$$

As for results (13) and (14), we have

$$\begin{aligned}\frac{\partial^2 ee_i}{\partial m_i^2} &= -\frac{2b_i(\alpha + N)\tilde{q}_i}{(b_i + 1)m_i^3(\alpha + N + \beta r_{ii})} < 0, \\ \frac{\partial^2 ee_i}{\partial \beta^2} &= -\frac{2b_i(\alpha + N)(m_i + \tilde{q}_i)r_{ii}^2}{(b_i + 1)m_i(\alpha + N + \beta r_{ii})^3} < 0, \\ \frac{\partial}{\partial N} \left( \frac{\partial ee_i}{\partial m_i} \right) &= \frac{b_i \tilde{q}_i \beta r_{ii}}{(b_i + 1)m_i^2(\alpha + N + \beta r_{ii})^2} > 0, \\ \frac{\partial}{\partial N} \left( \frac{\partial ee_i}{\partial \beta} \right) &= -\frac{b_i(m_i + \tilde{q}_i)r_{ii}(\alpha + N - \beta r_{ii})}{(b_i + 1)m_i(\alpha + N + \beta r_{ii})^3} < 0.\end{aligned}$$

## APPENDIX B

**Table B1: Definitions of Variables and Data Sources**

Variable		Definition	Source(s)
<b>Panel A: DEA model</b>			
Input	Labor	Size of employed population	CCSY (2004–2016)
Input	Capital	Total capital stock	Estimated by the perpetual inventory method, CCSY (2004–2016) and <i>China Statistical Yearbook</i> (CSY, 2004–2016)
Input	Land	Construction land area	CCSY (2004–2016)
Input	Energy	Primary energy consumption	GDP energy intensity (manually collected from various official documents) multiplied by GDP, <i>China Energy Statistical Yearbook</i> (CESY 2004–2016); Huang et al. (2018)
Desirable output	GDP	Gross domestic product	CCSY (2004–2016)
Undesirable output	EPI	Composite environmental pollution index	CCSY (2004–2016); CEY (2004–2016); Huang et al. (2018)
<b>Panel B: Econometric model</b>			
Dependent variable	<i>ee</i>	Eco-efficiency	Measured by Model (17)
Control variables	<i>pgdp</i>	Per capita GDP	CCSY (2004–2016)
	<i>wage</i>	Logarithm value of average salary	CCSY (2004–2016)
	<i>popd</i>	Population density	CCSY (2004–2016)
	<i>sfdi</i>	The ratio of FDI to GDP	CCSY (2004–2016)
	<i>sind</i>	The percentage of GDP contributed by the secondary industry sector	CCSY (2004–2016)
	<i>inno</i>	City innovation	Kou and Liu (2017)
	<i>er</i>	Environmental regulation	CCSY (2004–2016)

## APPENDIX C: ROBUSTNESS CHECKS: ALTERNATIVE MEASURE OF ECO-EFFICIENCY

**Table C1: Estimation Results for Different Periods: Full Sample**

Variable	2003–2015		2003–2010		2011–2015	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.3428*** (−7.4022)	−0.3103*** (−6.8630)	−0.6012*** (−8.3283)	−0.6780*** (−9.3292)	−0.4225*** (−5.4546)	−0.3098*** (−4.1369)
$\rho_2$	0.6297*** (12.7283)	0.5387*** (11.3725)	0.5670*** (7.2437)	0.5218*** (6.5945)	0.8362*** (10.4018)	0.6613*** (8.6647)
<i>pgdp</i>	0.0118*** (7.2420)	0.0134*** (8.2464)	0.0212*** (7.5770)	0.0214*** (7.6611)	0.0129*** (3.8216)	0.0133*** (4.0397)
<i>wage</i>	0.0904*** (5.9655)	0.0834*** (5.4909)	0.0803*** (4.6492)	0.0765*** (4.4015)	0.0343 (1.2568)	0.0495* (1.8467)
<i>popd</i>	1.1843*** (3.7212)	1.0793*** (3.3896)	1.0535*** (2.9746)	0.9880*** (2.7789)	1.0586 (1.3064)	1.3534* (1.6945)
<i>sfdi</i>	0.0108 (0.3079)	0.0103 (0.2972)	−0.1480*** (−2.9585)	−0.1259** (−2.5173)	−0.0225 (−0.3861)	0.0014 (0.0239)
<i>sind</i>	−0.0661 (−1.2428)	−0.1047** (−1.9699)	−0.1045 (−1.3522)	−0.1407* (−1.8177)	−0.0538 (−0.5738)	−0.0292 (−0.3156)
<i>inno</i>	0.0284*** (3.5508)	0.0276*** (3.4245)	−0.0595* (−1.6752)	−0.0102 (−0.2855)	0.0162 (1.3719)	0.0249** (2.1372)
<i>er</i>	0.0096 (0.5877)	0.0112 (0.6866)	−0.0096 (−0.4084)	−0.0154 (−0.6578)	0.0262 (1.2251)	0.0278 (1.3188)
Observations	2,483	2,483	1,528	1,528	955	955
R-squared	0.8302	0.8286	0.8563	0.8542	0.9223	0.9235
Log-likelihood	3,049.5805	3,045.1621	1,988.4864	1,989.5981	1,598.9133	1,608.2151

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table C2: Estimation Results for Different Periods: Eastern Cities**

Variable	2003–2015		2003–2010		2011–2015	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.6369*** (−6.1724)	−0.5547*** (−5.6238)	−1.4269*** (−6.8649)	−1.3838*** (−6.7614)	−0.3927** (−2.5405)	−0.2485* (−1.7210)
$\rho_2$	0.3183*** (3.5191)	0.2837*** (3.1673)	−0.3936* (−1.9060)	−0.3991* (−1.8608)	0.4815*** (3.8306)	0.3528*** (2.8361)
<i>pgdp</i>	0.0112*** (5.3242)	0.0122*** (5.7902)	0.0255*** (7.8725)	0.0254*** (7.5945)	0.0039 (0.6602)	0.0079 (1.4405)
<i>wage</i>	0.1368*** (2.9499)	0.1236*** (2.6574)	0.1607** (2.2706)	0.1546** (2.1266)	0.2028*** (2.6883)	0.1942 (2.7799)
<i>popd</i>	0.9831*** (2.8940)	0.9758*** (2.8661)	0.8820** (2.4983)	0.8200** (2.2667)	1.5674 (0.9922)	1.4552 (1.0014)
<i>sfdi</i>	−0.0255 (−0.5969)	−0.0273 (−0.6351)	−0.2240*** (−3.9289)	−0.1875*** (−3.2237)	0.0935 (0.8308)	0.1218 (1.1737)
<i>sind</i>	−0.2243** (−2.2626)	−0.2466** (−2.4772)	0.0215 (0.1628)	0.0150 (0.1111)	−0.9367*** (−2.6633)	−0.9868*** (−3.0335)
<i>inno</i>	0.0254*** (2.9376)	0.0216** (2.4679)	−0.0497 (−1.2821)	0.0023 (0.0583)	0.0066 (0.3421)	0.0184 (1.0366)
<i>er</i>	0.0050 (0.1859)	−0.0030 (−0.1128)	−0.0341 (−1.0051)	−0.0393 (−1.1327)	0.0554 (1.0201)	0.0096 (0.1897)
Observations	923	923	568	568	355	355
R-squared	0.8641	0.8635	0.8686	0.8620	0.9087	0.9218
Log-likelihood	1,162.1211	1,158.8959	788.2658	774.6058	486.5910	513.2557

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table C3: Estimation Results for Different Periods: Central/Western Cities**

Variable	2003–2015		2003–2010		2011–2015	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	–0.3209*** (–5.4100)	–0.3438*** (–5.6543)	–0.5592*** (–6.6471)	–0.5624*** (–6.6083)	–0.2909*** (–3.5076)	–0.3108*** (–3.6347)
$\rho_2$	0.6260*** (9.0413)	0.5925*** (8.5919)	0.6913*** (7.2847)	0.6580*** (6.9685)	0.9817*** (10.5944)	0.9307*** (10.0887)
<i>pgdp</i>	0.0199*** (5.9539)	0.0201*** (6.0449)	0.0184*** (2.7660)	0.0194*** (2.9439)	0.0299*** (8.6140)	0.0302*** (8.7209)
<i>wage</i>	0.0874*** (5.4343)	0.0842*** (5.2334)	0.0818*** (4.5099)	0.0777*** (4.2995)	–0.0156 (–0.8840)	–0.0160 (–0.9084)
<i>popd</i>	3.3999*** (3.4944)	3.4084*** (3.5095)	1.4807 (0.7755)	1.3506 (0.7110)	1.6535** (2.4813)	1.6609** (2.4933)
<i>sfdi</i>	–0.0249 (–0.3622)	–0.0243 (–0.3532)	–0.0464 (–0.4293)	–0.0205 (–0.1903)	–0.0753 (–1.3593)	–0.0617 (–1.1136)
<i>sind</i>	0.0132 (0.2039)	–0.0176 (–0.2713)	–0.1883* (–1.9123)	–0.2216** (–2.2640)	0.1054* (1.8476)	0.1241** (2.1774)
<i>inno</i>	0.1485*** (4.2218)	0.1510*** (4.2948)	0.5039*** (2.8141)	0.5256*** (2.9491)	0.1096*** (4.2909)	0.1098*** (4.3025)
<i>er</i>	0.0216 (1.0411)	0.0285 (1.3789)	0.0116 (0.3595)	–0.0018 (–0.0545)	–0.0022 (–0.1552)	0.0023 (0.1625)
Observations	1,560	1,560	960	960	600	600
R-squared	0.7899	0.7902	0.8476	0.8489	0.9488	0.9488
Log-likelihood	1,915.9532	1,920.8198	1,232.6034	1,237.0253	1,344.4720	1,345.9532

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table C4: Estimation Results for Different Periods: KEP Cities**

Variable	2003–2015		2003–2010		2011–2015	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	–0.3192*** (–6.5814)	–0.3130*** (–6.3501)	–0.5518*** (–7.8627)	–0.5803*** (–8.1817)	–0.5461*** (–5.8105)	–0.4065*** (–4.3952)
$\rho_2$	0.6251*** (12.8856)	0.5669*** (11.9720)	0.7214*** (10.1114)	0.7347*** (10.1925)	0.5667*** (6.2993)	0.4154*** (4.9261)
<i>pgdp</i>	0.0106*** (5.2271)	0.0121*** (5.9993)	0.0109*** (3.1962)	0.0099*** (2.8546)	0.0151*** (3.3360)	0.0143*** (3.2355)
<i>wage</i>	0.0976*** (3.4667)	0.0939*** (3.3065)	0.0716** (2.2635)	0.0678** (2.1305)	0.0543 (1.1217)	0.0561 (1.1783)
<i>popd</i>	1.3035** (2.1555)	1.2316** (2.0206)	1.8431* (1.6780)	0.8638 (0.7833)	1.0238 (1.0059)	1.0261 (1.0308)
<i>sfdi</i>	0.0137 (0.3736)	0.0035 (0.0953)	–0.1575*** (–3.2215)	–0.1272*** (–2.5877)	–0.0999 (–1.4253)	–0.0972 (–1.4094)
<i>sind</i>	0.0499 (0.6460)	0.0221 (0.2834)	–0.0119 (–0.1265)	–0.0191 (–0.2016)	0.2080 (1.1652)	0.2656 (1.5121)
<i>inno</i>	0.0337*** (4.1417)	0.0323*** (3.9206)	–0.0227 (–0.6759)	0.0444 (1.3284)	0.0117 (0.8934)	0.0226* (1.7631)
<i>er</i>	0.0330 (1.5004)	0.0313 (1.4095)	–0.0221 (–0.7799)	–0.0352 (–1.2346)	0.0252 (0.7633)	0.0247 (0.7615)
Observations	1,521	1,521	936	936	585	585
R-squared	0.8676	0.8656	0.9047	0.9037	0.9281	0.9304
Log-likelihood	1,976.6216	1,970.1381	1,389.8528	1,387.1780	962.3307	969.0667

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table C5: Estimation Results for Different Periods: Non-KEP Cities**

Variable	2003–2015		2003–2010		2011–2015	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.3322*** (−4.2525)	−0.3368*** (−4.1955)	−0.5409*** (−4.7261)	−0.5075*** (−4.3994)	−0.8947*** (−5.5635)	−0.4449*** (−3.2470)
$\rho_2$	0.4911*** (7.4421)	0.4485*** (6.5867)	0.5071*** (5.6729)	0.4356*** (4.6359)	0.7812*** (12.0694)	0.5723*** (5.5533)
<i>pgdp</i>	0.0275*** (6.5041)	0.0273*** (6.4361)	0.0361*** (5.9290)	0.0373*** (6.1443)	0.0022 (0.1889)	0.0047 (0.4079)
<i>wage</i>	0.0696*** (3.5845)	0.0671*** (3.4456)	0.0877*** (3.8060)	0.0839*** (3.6318)	−0.0337 (−1.1830)	−0.0386 (−1.3362)
<i>popd</i>	1.1239*** (2.7742)	1.1672*** (2.8726)	1.3378*** (2.9895)	1.3588*** (3.0364)	−1.0647 (−0.8311)	−1.2596 (−0.9742)
<i>sfdi</i>	−0.0729 (−0.8084)	−0.0695 (−0.7688)	0.0258 (0.1850)	0.0673 (0.4831)	−0.0804 (−0.6779)	−0.0602 (−0.5022)
<i>sind</i>	−0.3093*** (−3.6517)	−0.3475*** (−4.0982)	−0.2941** (−2.0857)	−0.3538** (−2.5200)	−0.1519 (−1.5808)	−0.1489 (−1.5377)
<i>inno</i>	−1.5013*** (−6.6829)	−1.3712*** (−6.0520)	−3.5495 (−1.5458)	−3.6178 (−1.5766)	−0.9904*** (−3.5420)	−1.0722*** (−3.7853)
<i>er</i>	−0.0249 (−0.9437)	−0.0169 (−0.6377)	−0.0069 (−0.1693)	−0.0142 (−0.3467)	0.0243 (0.9928)	0.0244 (0.9862)
Observations	962	962	592	592	370	370
R-squared	0.7902	0.7890	0.8070	0.8070	0.9297	0.9284
Log-likelihood	1,158.6718	1,156.1296	696.6822	695.7065	740.0271	727.2455

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table C6: Estimation Results for Different Periods: RB Cities**

Variable	2003–2015		2003–2010		2011–2015	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.1390** (−2.4530)	−0.1510*** (−2.6349)	−0.3480*** (−4.0354)	−0.3582*** (−4.1264)	−0.0450 (−0.6172)	−0.0348 (−0.4839)
$\rho_2$	0.4824*** (10.7708)	0.4822*** (10.9091)	0.5923*** (10.8844)	0.5773*** (10.4419)	0.8610*** (27.4293)	0.8488*** (25.2104)
<i>pgdp</i>	0.0190*** (5.5503)	0.0196*** (5.7378)	0.0198*** (2.7613)	0.0207*** (2.9255)	0.0311*** (9.8594)	0.0316*** (10.0333)
<i>wage</i>	0.0657*** (3.5370)	0.0658*** (3.5330)	0.0600*** (2.9658)	0.0591*** (2.9257)	−0.0222 (−1.2119)	−0.0192 (−1.0502)
<i>popd</i>	4.8435* (1.9406)	5.4196** (2.1654)	6.5617* (1.8118)	7.5701** (2.0941)	−7.0118** (−2.2746)	−7.1183** (−2.3088)
<i>sfdi</i>	−0.0791 (−0.7729)	−0.0488 (−0.4748)	−0.0125 (−0.0990)	0.0482 (0.3824)	0.0114 (0.1600)	0.0280 (0.3915)
<i>sind</i>	0.0269 (0.3261)	−0.0095 (−0.1140)	0.0406 (0.3506)	−0.0181 (−0.1568)	0.0718 (1.1304)	0.0779 (1.2259)
<i>inno</i>	0.2824 (1.2817)	0.2093 (0.9482)	1.6516 (1.3110)	1.3571 (1.0824)	−0.3932*** (−3.0411)	−0.4005*** (−3.0923)
<i>er</i>	0.0314 (1.0822)	0.0315 (1.0824)	−0.0098 (−0.2175)	−0.0108 (−0.2394)	−0.0079 (−0.4663)	−0.0139 (−0.8271)
Observations	1014	1014	624	624	390	390
R-squared	0.7824	0.7815	0.8509	0.8514	0.9521	0.9521
Log-likelihood	1321.7205	1318.8161	847.8766	848.7807	964.8801	962.4305

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table C7: Estimation Results for Different Periods: Non-RB Cities**

Variable	2003–2015		2003–2010		2011–2015	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.5935*** (−9.0244)	−0.5674*** (−8.6124)	−0.7465*** (−7.7610)	−0.7676*** (−7.8119)	−0.7987*** (−6.1041)	−0.6532*** (−5.2786)
$\rho_2$	0.2769*** (5.5221)	0.2245*** (4.3644)	0.1365* (1.7268)	0.0914 (1.1046)	0.1653* (1.8295)	0.0890 (0.9934)
<i>pgdp</i>	0.0124*** (5.7809)	0.0133*** (6.2368)	0.0254*** (7.2804)	0.0247*** (6.9900)	0.0045 (0.7723)	0.0072 (1.2940)
<i>wage</i>	0.1430*** (4.5402)	0.1358*** (4.3150)	0.1236*** (2.9570)	0.1259*** (2.9829)	0.0587 (1.0820)	0.0535 (1.0316)
<i>popd</i>	0.9962*** (2.9174)	0.9430*** (2.7649)	1.0326*** (2.7216)	0.9559** (2.4946)	0.5993 (0.5518)	0.8721 (0.8431)
<i>sfdi</i>	0.0226 (0.5278)	0.0112 (0.2625)	−0.0941 (−1.5306)	−0.0617 (−0.9941)	−0.0771 (−0.8005)	−0.0885 (−0.9638)
<i>sind</i>	−0.2382*** (−2.9299)	−0.2751*** (−3.3938)	−0.1715 (−1.4218)	−0.1919 (−1.5715)	−0.3426 (−1.6372)	−0.2891 (−1.4469)
<i>inno</i>	0.0331*** (3.8488)	0.0308*** (3.5714)	−0.0537 (−1.3688)	−0.0015 (−0.0374)	0.0300* (1.9115)	0.0354** (2.3578)
<i>er</i>	0.0114 (0.5205)	0.0090 (0.4122)	0.0040 (0.1301)	−0.0061 (−0.1941)	0.0285 (0.8010)	0.0364 (1.0738)
Observations	1,469	1,469	904	904	565	565
R-squared	0.8367	0.8371	0.8507	0.8477	0.8961	0.9052
Log-likelihood	1,800.9122	1,806.4777	1,174.2957	1,170.7943	839.98095	862.7707

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table C8: Estimation Results for Different Periods: TCZ Cities**

Variable	2003–2015		2003–2010		2011–2015	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.3134*** (−6.4841)	−0.3015*** (−6.2484)	−0.6606*** (−9.3656)	−0.6737*** (−9.5476)	−0.5534*** (−5.5487)	−0.4204*** (−4.4072)
$\rho_2$	0.7155*** (14.4347)	0.6841*** (13.8075)	0.9683*** (14.4208)	1.0049*** (14.2387)	0.5549*** (5.4453)	0.4231*** (4.2604)
<i>pgdp</i>	0.0143*** (7.8204)	0.0158*** (8.7026)	0.0270*** (10.0712)	0.0270*** (9.9325)	0.0032 (0.7250)	0.0049 (1.1495)
<i>wage</i>	0.1576*** (4.8902)	0.1554*** (4.8269)	0.0661 (1.5202)	0.0705 (1.6123)	0.0982** (2.1592)	0.0981** (2.2346)
<i>popd</i>	1.1990*** (3.9130)	1.1897*** (3.8877)	0.9680*** (3.1896)	0.8806*** (2.8857)	0.4944 (0.4663)	0.4847 (0.4753)
<i>sfdi</i>	0.0255 (0.6623)	0.0148 (0.3851)	−0.2037*** (−4.1884)	−0.1754 (−3.5958)	−0.0581 (−0.7219)	−0.0467 (−0.6009)
<i>sind</i>	−0.0184 (−0.2591)	−0.0302 (−0.4251)	0.0637 (0.7196)	0.0733 (0.8223)	−0.1379 (−0.6701)	−0.0186 (−0.0935)
<i>inno</i>	0.0339*** (4.4231)	0.0310*** (4.0200)	−0.0700** (−2.2520)	−0.0056 (−0.1817)	0.0241* (1.7651)	0.0329** (2.4897)
<i>er</i>	0.0132 (0.6601)	0.0169 (0.8454)	−0.0411 (−1.5953)	−0.0444* (−1.7092)	0.0160 (0.5173)	0.0229 (0.7665)
Observations	1,651	1,651	1,016	1,016	635	635
R-squared	0.8564	0.8568	0.8975	0.8963	0.9157	0.9214
Log-likelihood	2,120.2997	2,123.2639	1,482.0985	1,476.1617	1,025.2875	1,043.9151

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.



**Table C9: Estimation Results for Different Periods: Non-TCZ Cities**

Variable	2003–2015		2003–2010		2011–2015	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.1212*	−0.1344**	−0.1836**	−0.1777**	−0.4715***	−0.4696***
	(−1.8194)	(−1.9768)	(−2.0413)	(−1.9661)	(−3.6012)	(−3.5805)
$\rho_2$	0.3757***	0.3665***	0.3367***	0.3241***	0.7047***	0.6889***
	(7.6619)	(7.4942)	(5.0823)	(4.8882)	(17.1239)	(15.9910)
<i>pgdp</i>	0.0230***	0.0253***	0.0254**	0.0295**	0.0369***	0.0389***
	(4.3663)	(4.8779)	(2.0224)	(2.4222)	(4.6346)	(4.8580)
<i>wage</i>	0.0490**	0.0426**	0.0617***	0.0544**	−0.0220	−0.0229
	(2.5300)	(2.1949)	(2.7454)	(2.4283)	(−0.7739)	(−0.7922)
<i>popd</i>	0.1056	0.1964	−1.2364	−1.4920	−0.1334	−0.1068
	(0.0474)	(0.0880)	(−0.2332)	(−0.2833)	(−0.1118)	(−0.0884)
<i>sfdi</i>	−0.0429	−0.0568	0.1164	0.1342	−0.0224	−0.0503
	(−0.3466)	(−0.4587)	(0.6466)	(0.7493)	(−0.1431)	(−0.3185)
<i>sind</i>	−0.3094***	−0.3652***	−0.4959***	−0.5503***	−0.0817	−0.0667
	(−3.3863)	(−3.9940)	(−3.2276)	(−3.6176)	(−0.9712)	(−0.7840)
<i>inno</i>	0.3312***	0.2986***	1.0508**	1.0658**	0.0060	−0.0192
	(2.8784)	(2.5921)	(1.9927)	(2.0320)	(0.0497)	(−0.1573)
<i>er</i>	−0.0055	−0.0100	0.0284	0.0192	0.0276	0.0253
	(−0.1768)	(−0.3212)	(0.5836)	(0.3966)	(0.9724)	(0.8837)
Observations	832	832	512	512	320	320
R-squared	0.8083	0.8077	0.8250	0.8269	0.9524	0.9512
Log-likelihood	978.7677	978.8077	599.5602	601.8643	642.0050	637.9659

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

## APPENDIX D: ESTIMATION RESULTS OF DIFFERENT CITIES: PERIOD 2003–2015

Table D1: Eastern vs. Central/Western

Variable	Eastern		Central/Western	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.5870*** (−5.8525)	−0.5894*** (−6.0344)	−0.2362*** (−4.5447)	−0.2375*** (−4.4928)
$\rho_2$	0.3302*** (3.8962)	0.3547*** (4.0491)	0.8213*** (13.8975)	0.7818*** (13.2364)
<i>pgdp</i>	0.0079*** (3.7583)	0.0079*** (3.7737)	0.0214*** (15.1682)	0.0214*** (6.2739)
<i>wage</i>	0.1085** (2.3171)	0.0978** (2.0868)	0.0782*** (6.2412)	0.0748*** (4.4372)
<i>popd</i>	0.4535 (1.3173)	0.4457 (1.2946)	3.9841*** (4.6400)	4.1446*** (4.1191)
<i>sfdi</i>	−0.0050 (−0.1164)	−0.0003 (−0.0080)	−0.0166*** (3.9545)	−0.0181 (−0.2515)
<i>sind</i>	−0.2254** (−2.2442)	−0.2120** (−2.1105)	0.0013 (−0.2314)	−0.0230 (−0.3381)
<i>inno</i>	0.0261*** (2.9709)	0.0258*** (2.9360)	0.1075 (0.0194)	0.1027*** (2.7873)
<i>er</i>	0.0015 (0.0557)	−0.0055 (−0.2024)	0.0182*** (2.9184)	0.0268 (1.2406)
Observations	923	923	1,560	1,560
R-squared	0.8848	0.8847	0.8269	0.8271
Log-likelihood	1,144.5527	1,146.4509	1,806.2240	1,808.2883

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Table D2: KEP vs. Non-KEP

Variable	KEP		Non-KEP	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.2511*** (−5.4088)	−0.2407*** (−5.1671)	−0.3052*** (−4.0535)	−0.3086*** (−4.0496)
$\rho_2$	0.6990*** (14.7796)	0.6718*** (14.6059)	0.6346*** (11.6215)	0.6063*** (10.8427)
<i>pgdp</i>	0.0110*** (5.2326)	0.0123*** (5.8786)	0.0192*** (4.4083)	0.0187*** (4.3082)
<i>wage</i>	0.0978*** (3.2916)	0.0910*** (3.0573)	0.0628*** (3.1142)	0.0566*** (2.8051)
<i>popd</i>	1.0329 (1.6208)	0.9448 (1.4799)	0.4605 (1.0950)	0.5050 (1.2008)
<i>sfdi</i>	−0.0060 (−0.1546)	−0.0009 (−0.0241)	0.0856 (0.9122)	0.0806 (0.8590)
<i>sind</i>	−0.0379 (−0.4646)	−0.0325 (−0.3973)	−0.2702*** (−3.0766)	−0.2909*** (−3.3136)
<i>inno</i>	0.0310*** (3.6112)	0.0309*** (3.5820)	−1.2083*** (−5.1722)	−1.2066*** (−5.1657)
<i>er</i>	0.0298 (1.2839)	0.0448* (1.9239)	−0.0130 (−0.4738)	−0.0216 (−0.7871)
Observations	1,521	1,521	962	962
R-squared	0.8702	0.8697	0.8501	0.8501
Log-likelihood	1,866.8973	1,865.9818	1,097.4344	1,099.1105

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

**Table D3: RB vs. Non-RB**

Variable	RB		Non-RB	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.1422** (−2.4412)	−0.1444** (−2.5053)	−0.4700*** (−7.5715)	−0.4732*** (−7.6169)
$\rho_2$	0.5134*** (12.8331)	0.5329*** (13.4887)	0.4008*** (8.7949)	0.3858*** (8.3367)
<i>pgdp</i>	0.0196*** (5.5145)	0.0196*** (5.5320)	0.0096*** (4.2949)	0.0099*** (4.3962)
<i>wage</i>	0.0671*** (3.4240)	0.0651*** (3.3305)	0.1028*** (3.0800)	0.0974*** (2.9245)
<i>popd</i>	0.6335 (0.2408)	1.2652 (0.4815)	0.6200* (1.7169)	0.6130* (1.7016)
<i>sfdi</i>	−0.1011 (−0.9319)	−0.1278 (−1.1821)	0.0177 (0.3914)	0.0224 (0.4970)
<i>sind</i>	−0.0234 (−0.2678)	−0.0206 (−0.2367)	−0.1754** (−2.0342)	−0.1969** (−2.2914)
<i>inno</i>	0.1798 (0.7742)	0.2117 (0.9120)	0.0340*** (3.7343)	0.0332*** (3.6494)
<i>er</i>	0.0422 (1.3792)	0.0438 (1.4349)	−0.0045 (−0.1938)	−0.0036 (−0.1536)
Observations	1,014	1,014	1,469	1,469
R-squared	0.8073	0.8083	0.8545	0.8553
Log-likelihood	1,249.7578	1,250.3684	1,678.2092	1,686.3337

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table D4: TCZ vs. Non-TCZ**

Variable	TCZ		Non-TCZ	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.2823*** (−5.9947)	−0.2808*** (−5.9355)	−0.0531 (−0.8520)	−0.0597 (−0.9532)
$\rho_2$	0.7903*** (20.8294)	0.7693*** (19.1219)	0.4728*** (11.2262)	0.4736*** (11.2895)
<i>pgdp</i>	0.0119*** (6.4298)	0.0124*** (6.6912)	0.0119*** (6.4298)	0.0260*** (4.9870)
<i>wage</i>	0.1545*** (4.6431)	0.1480*** (4.4249)	0.1545*** (4.6431)	0.0306 (1.5412)
<i>popd</i>	0.7262** (2.2942)	0.7516** (2.3652)	0.7262** (2.2942)	1.6766 (0.7356)
<i>sfdi</i>	0.0225 (0.5664)	0.0325 (0.8173)	0.0225 (0.5664)	−0.0522 (−0.4128)
<i>sind</i>	−0.0454 (−0.6174)	−0.0560 (−0.7582)	−0.0454 (−0.6174)	−0.3393*** (−3.6325)
<i>inno</i>	0.0362*** (4.5733)	0.0352*** (4.4081)	0.0362*** (4.5733)	0.2297* (1.9517)
<i>er</i>	0.0012 (0.0584)	0.0087 (0.4191)	0.0012 (0.0584)	−0.0003 (−0.0095)
Observations	1,651	1,651	832	832
R-squared	0.8686	0.8675	0.8628	0.8630
Log-likelihood	2,038.0913	2,035.7453	929.9410	930.9586

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

## APPENDIX E: ESTIMATION RESULTS OF DIFFERENT CITIES: PERIOD 2003–2010

**Table E1: Eastern vs. Central/Western**

Variable	Eastern		Central/Western	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.7607*** (−4.6806)	−0.8090*** (−5.2195)	−0.3437*** (−4.7367)	−0.3508*** (−4.7877)
$\rho_2$	−0.0028 (−0.0187)	0.1513 (0.9469)	0.7754*** (9.1725)	0.7612*** (9.1517)
<i>pgdp</i>	0.0165*** (5.1160)	0.0156*** (4.8303)	0.0207* (3.0350)	0.0229*** (3.3585)
<i>wage</i>	0.1071 (1.5021)	0.0887 (1.2443)	0.0806** (4.2974)	0.0761*** (4.0370)
<i>popd</i>	0.3128 (0.8754)	0.1983 (0.5551)	2.5195 (1.2854)	3.1350 (1.5978)
<i>sfdi</i>	−0.1409** (−2.4534)	−0.1163 (−2.0227)	0.0689 (0.6130)	0.0300 (0.2664)
<i>sind</i>	−0.0124 (−0.0930)	0.0662 (0.4976)	−0.2096** (−2.0591)	−0.2186** (−2.1424)
<i>inno</i>	−0.0100 (−0.2558)	0.0492 (1.2602)	0.3602* (1.9418)	0.3459* (1.8601)
<i>er</i>	−0.0542 (−1.5783)	−0.0564 (−1.6447)	0.0448 (1.3375)	0.0385 (1.1462)
Observations	568	568	960	960
R-squared	0.9003	0.9004	0.8664	0.8657
Log-likelihood	759.9461	760.0912	1,174.0369	1,170.8136

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table E2: KEP vs. Non-KEP**

Variable	KEP		Non-KEP	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.4297*** (−6.3680)	−0.4360** (−6.5150)	−0.3786*** (−3.6703)	−0.3884*** (−3.6892)
$\rho_2$	0.7164*** (10.0129)	0.7505*** (10.5090)	0.5750*** (7.3323)	0.5550*** (7.0480)
<i>pgdp</i>	0.0087** (2.2805)	0.0078* (2.0361)	0.0235*** (4.0616)	0.0231*** (3.9670)
<i>wage</i>	0.0880** (2.4633)	0.0793** (2.2329)	0.0789*** (3.5330)	0.0720*** (3.1928)
<i>popd</i>	2.2845* (1.8366)	1.1904 (0.9640)	0.5435 (1.2569)	0.5184 (1.1913)
<i>sfdi</i>	−0.0890 (−1.6085)	−0.0712 (−1.2899)	0.1996 (1.4781)	0.1599 (1.1774)
<i>sind</i>	−0.1770* (−1.6634)	−0.1575 (−1.4895)	−0.1236 (−0.9114)	−0.0917 (−0.6717)
<i>inno</i>	−0.0254 (−0.6732)	0.0467 (1.2505)	−1.4665 (−0.6610)	−1.6404 (−0.7349)
<i>er</i>	−0.0027 (−0.0845)	−0.0111 (−0.3491)	0.0050 (0.1269)	−0.0005 (−0.0132)
Observations	936	936	592	592
R-squared	0.8943	0.8955	0.8758	0.8742
Log-likelihood	1,262.4693	1,266.2828	697.8236	694.4534

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table E3: RB vs. Non-RB**

Variable	RB		Non-RB	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.2455*** (−2.9761)	−0.2642*** (−3.1662)	−0.5395*** (−6.1881)	−0.5499*** (−6.3499)
$\rho_2$	0.5464*** (10.5832)	0.5576*** (10.9807)	0.2283*** (3.1311)	0.2527*** (3.4664)
<i>pgdp</i>	0.0283*** (3.9308)	0.0309*** (4.2601)	0.0157*** (4.3900)	0.0143*** (4.0184)
<i>wage</i>	0.0593*** (2.8104)	0.0565*** (2.6514)	0.0932** (2.1540)	0.0859** (1.9994)
<i>popd</i>	5.5036 (1.4576)	5.1712 (1.3568)	0.4439 (1.1324)	0.3707 (0.9521)
<i>sfdi</i>	0.1106 (0.8325)	0.0546 (0.4089)	−0.0147 (−0.2313)	0.0093 (0.1479)
<i>sind</i>	−0.0634 (−0.5256)	−0.0312 (−0.2559)	−0.1971 (−1.5826)	−0.1869 (−1.5091)
<i>inno</i>	−0.8965 (−0.6837)	−0.3288 (−0.2471)	0.0018 (0.0450)	0.0525 (1.3139)
<i>er</i>	0.0453 (0.9627)	0.0541 (1.1398)	−0.0137 (−0.4265)	−0.0217 (−0.6811)
Observations	624	624	904	904
R-squared	0.8637	0.8612	0.8774	0.8791
Log-likelihood	805.6785	799.5646	1,118.7112	1,125.791

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table E4: TCZ vs. Non-TCZ**

Variable	TCZ		Non-TCZ	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.4833*** (−7.9945)	−0.4893*** (−8.1285)	−0.0073 (−0.0910)	−0.0094 (−0.1176)
$\rho_2$	1.0899*** (30.5949)	1.1365*** (24.3467)	0.2731*** (3.9849)	0.2812*** (4.1590)
<i>pgdp</i>	0.0192*** (6.6686)	0.0183*** (6.3797)	0.0235** (2.0069)	0.0271** (2.3278)
<i>wage</i>	0.0899* (1.9125)	0.0705 (1.4996)	0.0513** (2.3763)	0.0437** (2.0156)
<i>popd</i>	0.3983 (1.2087)	0.2697 (0.8204)	−1.5981 (−0.3145)	−0.4488 (−0.0885)
<i>sfdi</i>	−0.1101** (−2.0911)	−0.0924* (−1.7566)	0.0909 (0.5248)	0.0984 (0.5675)
<i>sind</i>	−0.0532 (−0.5521)	−0.0021 (−0.0216)	−0.4206*** (−2.8656)	−0.4021*** (−2.7360)
<i>inno</i>	−0.0234 (−0.6958)	0.0497 (1.4910)	0.9547* (1.8847)	0.9306* (1.8362)
<i>er</i>	−0.0417 (−1.4897)	−0.0415 (−1.4859)	0.0878* (1.8782)	0.0831* (1.7768)
Observations	1,016	1,016	512	512
R-squared	0.8995	0.9000	0.8606	0.8604
Log-likelihood	1,360.8747	1,363.0774	609.7308	608.4771

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

## APPENDIX F: ESTIMATION RESULTS OF DIFFERENT CITIES: PERIOD 2011–2015

Table F1: Eastern vs. Central/Western

Variable	Eastern		Central/Western	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.4863*** (−3.1425)	−0.3689** (−2.5292)	−0.5228*** (−5.5975)	−0.5096*** (−5.2609)
$\rho_2$	0.4412*** (3.5798)	0.3584*** (2.8359)	1.0610*** (10.8509)	0.9746*** (9.5713)
<i>pgdp</i>	0.0010 (0.1858)	0.0014 (0.2645)	0.0421*** (7.4781)	0.0423*** (7.5003)
<i>wage</i>	0.2027** (2.7932)	0.1969*** (2.8218)	−0.0336 (−1.1707)	−0.0291 (−1.0088)
<i>popd</i>	0.7254 (0.4796)	0.2717 (0.1865)	3.0384*** (2.7918)	3.0284*** (2.7755)
<i>sfdi</i>	0.0885 (0.8214)	0.0846 (0.8156)	−0.1800** (−1.9812)	−0.1729* (−1.8981)
<i>sind</i>	−1.0153*** (−3.0088)	−0.9761*** (−3.0022)	0.2857*** (3.0629)	0.2890*** (3.0897)
<i>inno</i>	−0.0025 (−0.1352)	0.0062 (0.3470)	0.0489 (1.1680)	0.0503 (1.1999)
<i>er</i>	0.0291 (0.5590)	0.0200 (0.3996)	0.0054 (0.2311)	0.0119 (0.5073)
Observations	355	355	600	600
R-squared	0.9209	0.9266	0.9251	0.9247
Log-likelihood	503.3465	516.6078	1,058.9339	1,059.1219

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

Table F2: KEP vs. Non-KEP

Variable	KEP		Non-KEP	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	−0.4841*** (−5.4242)	−0.3985*** (−4.4300)	−0.7945*** (−5.0447)	−0.7476*** (−4.8923)
$\rho_2$	0.6497*** (7.6882)	0.5217*** (6.2234)	0.7866*** (12.4526)	0.7860*** (12.4599)
<i>pgdp</i>	0.0141*** (2.8725)	0.0148*** (3.0274)	0.0214 (1.3531)	0.0226 (1.4635)
<i>wage</i>	0.0254 (0.4798)	0.0292 (0.5547)	−0.0370 (−0.9381)	−0.0249 (−0.6460)
<i>popd</i>	0.4664 (0.4205)	0.2865 (0.2590)	3.1221** (1.7650)	3.3047* (1.9190)
<i>sfdi</i>	−0.1366* (−1.7816)	−0.1277* (−1.6702)	−0.1119 (−0.6858)	−0.1126 (−0.7091)
<i>sind</i>	0.4329** (2.2206)	0.5057*** (2.5997)	−0.0771 (−0.5838)	−0.1011 (−0.7859)
<i>inno</i>	0.0041 (0.2927)	0.0125 (0.8847)	−1.4457*** (−3.7352)	−1.3966* (−3.7068)
<i>er</i>	0.0234 (0.6518)	0.0354 (0.9855)	0.0342 (1.0106)	0.0386 (1.1737)
Observations	585	585	370	370
R-squared	0.9236	0.9239	0.9233	0.9274
Log-likelihood	902.5423	904.1734	613.0127	621.3885

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table F3: RB vs. Non-RB**

Variable	RB		Non-RB	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	-0.1900** (-2.0422)	-0.1973** (-2.1635)	-0.6542*** (-5.4939)	-0.5709*** (-4.9006)
$\rho_2$	0.7763*** (19.4108)	0.8138*** (21.9443)	0.2560*** (3.0390)	0.1631* (1.8587)
<i>pgdp</i>	0.0376*** (7.4194)	0.0368*** (7.3152)	0.0038 (0.6023)	0.0058 (0.9418)
<i>wage</i>	-0.0049 (-0.1665)	-0.0037 (-0.1284)	0.0155 (0.2600)	0.0257 (0.4445)
<i>popd</i>	-6.8786 (-1.3966)	-5.9610 (-1.2154)	0.7061 (0.5927)	0.5177 (0.4465)
<i>sfdi</i>	-0.0441 (-0.3890)	-0.0283 (-0.2513)	-0.1540 (-1.4598)	-0.1734* (-1.6897)
<i>sind</i>	0.1715* (1.6863)	0.1765* (1.7470)	-0.0122 (-0.0530)	0.0792 (0.3539)
<i>inno</i>	-0.3664* (-1.7742)	-0.3116 (-1.5206)	0.0137 (0.8032)	0.0213 (1.2788)
<i>er</i>	-0.0410 (-1.5080)	-0.0411 (-1.5273)	0.0363 (0.9293)	0.0492 (1.2985)
Observations	390	390	565	565
R-squared	0.9295	0.9304	0.8955	0.9011
Log-likelihood	786.5486	791.6940	777.0803	793.6655

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

**Table F4: TCZ vs. Non-TCZ**

Variable	TCZ		Non-TCZ	
	<i>d</i>	$\tilde{d}$	<i>d</i>	$\tilde{d}$
$\rho_1$	-0.5084*** (-5.2750)	-0.4420*** (-4.5728)	-0.5830*** (-4.2768)	-0.5469*** (-4.1320)
$\rho_2$	0.5900*** (7.1936)	0.4564*** (5.0633)	0.7428*** (20.2935)	0.7428*** (20.4372)
<i>pgdp</i>	0.0000 (0.0023)	0.0011 (0.2350)	0.0590*** (5.6805)	0.0590*** (5.7818)
<i>wage</i>	0.0578 (1.1955)	0.0646 (1.3492)	-0.0287 (-0.7731)	-0.0247 (-0.6759)
<i>popd</i>	0.1644 (0.1468)	-0.1681 (-0.1511)	2.7098* (1.7414)	2.7659* (1.8035)
<i>sfdi</i>	-0.0660 (-0.7734)	-0.0703 (-0.8302)	-0.3641* (-1.7883)	-0.3666* (-1.8288)
<i>sind</i>	0.0978 (0.4475)	0.1249 (0.5759)	-0.0002 (-0.0016)	-0.0072 (-0.0670)
<i>inno</i>	0.0136 (0.9582)	0.0218 (1.5308)	-0.1388 (-0.8793)	-0.1336 (-0.8592)
<i>er</i>	0.0040 (0.1208)	0.0194 (0.5944)	0.0571 (1.5441)	0.0562 (1.5441)
Observations	635	635	320	320
R-squared	0.9147	0.9160	0.9521	0.9535
Log-likelihood	979.3877	986.7776	560.0429	563.2432

Notes: The t- statistics are given in parentheses. All regressions include spatial- and time period-fixed effects. Spatial lags of the control variables are not presented in order to save space. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.