**Impact of Environmental Regulations on Carbon Emissions of**

**Transportation Infrastructure: China’s Evidence**

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1. **Impact of Environmental Regulations on the Carbon Emissions**
2. **of Transportation Infrastructure: China’s Evidence**
3. **Abstract:** Environmental regulations (ER) can support or dissuade the reduction of
4. carbon emissions. However, there are limited studies on the impact of ER on carbon
5. emissions for the transportation infrastructure. Using provincial panel data from
6. China for the period 2001-2017, this study measures how ER can affect the carbon
7. emissions efficiency (CEE) of transportation infrastructure. The study uses Hansen’s
8. panel threshold model to analyze current thresholds of ER on CEE. The results show
9. that (1) China's transportation infrastructure during 2001-2017 experienced a 10.15%
10. decrease of CEE; (2) there are significant heterogeneities across the regions of China
11. regarding CEE; (3) ER produces some CEE threshold effects in China's current
12. transportation infrastructure. This study proposes alternative evaluation methods and
13. theoretical frameworks for dynamically measuring the CEE of transportation
14. infrastructure, and provides governments with improved criteria to design effective
15. environmental policies.

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1. **Keywords:** Transportation infrastructure; Carbon emission efficiency; Environmental
2. regulations; Low-carbon transition; Threshold model.

# 1 Introduction

1. According to the World Resources Institute (WRI), global greenhouse gas (GHG)
2. emissions increased from 31.78 billion (109) tons in 1990 to 47.57 billion tons in 2017
3. (WRI, 2017); of these GHG, CO2 emissions account for approximately 75%. As a
4. developing but responsible country, China has committed to limit CO2 emissions and
5. reach the peak CO2 emissions as early as 2030 (Zhou et al., 2019a). In this context,
6. various industries are facing greater pressure to reduce CO2 emissions. In China the
7. transportation is a major emitter of waste CO2. Indeed, the CO2 emissions for the
8. transportation infrastructure in China increased at an average annual rate of 15%
9. during the period 1997-2006 (Bai et al.). Hence, there is an urgent need for the
10. transportation infrastructure sector in China to undergo a low-carbon transition if the
11. country wants to meet its CO2 emissions reduction objectives.
12. Due to the existence of environmental externalities and market failures, the
13. government needs to adopt environmental regulations (ER) to solve the increasingly
14. serious environmental pollution problems (Zhang et al., 2020). However, some
15. scholars question the necessity for ER. For example, Schou (2002) argues that the
16. (negative) externality of environmental pollution will always remain under the control
17. of market mechanisms, dismissing ER as superfluous. In a similar vein, Sinn (2008)
18. believes that implementation of ER may actually lead to a further increase in CO2
19. emissions through decreasing CO2 emission efficiency. Therefore, to avoid potentially
20. opposite effects, it is important to have an improved understanding of how to measure
21. the cause and effect of ER on transportation infrastructure.
22. It has been postulated that increasing the carbon emissions efficiency (CEE) is
23. the key to achieve a low-carbon transportation infrastructure sector (Cao and Li,
24. 2014). However, the literature concerning evaluation of CEE has mostly adopted a
25. static perspective with less attention paid to the dynamic efficiency of carbon
26. emissions, especially for transportation infrastructure. Similarly, studies of the
27. impacts of ER on CEE are mainly concentrated in the industrial sector (Ouyang et al.,
28. 2020), manufacturing industry (Zhai and An, 2020), construction industry (Zhang et
29. al., 2018), and energy industry (Du et al., 2020). The impact of ER on the CEE of
30. transportation infrastructure remains relatively unexplored. Only by accurately
31. assessing the carbon emissions efficiency of transportation infrastructure and the
32. corresponding impact of environmental regulations can development policies be
33. formulated to achieve a low-carbon transformation of transportation infrastructure.
34. In response to the problems above, this research study adopts transportation
35. infrastructure as the research object. Based on the panel data of 30 Chinese provinces
36. and cities from 2001 to 2017, the study evaluates the dynamic carbon emissions
37. efficiency of transportation infrastructure according to both the national and regional
38. levels, which allows exploration of the threshold effect of environmental regulations
39. on the carbon emission efficiency of transportation infrastructure.
40. The main contributions of this paper are as follows: (1) According to the
41. dynamic perspective to measure the carbon emissions efficiency of transportation
42. infrastructure, this study applies a RAM-based global Malmquist-Luenberger
43. productivity index (GML) to dynamically evaluate the CEE of transportation
44. infrastructure. The study will improve current evaluation methods and theoretical
45. frameworks to measure CEE in transportation infrastructure. (2) The study analyzes
46. the threshold effects of ER on CEE of Chinese transportation infrastructure, thereby
47. clarifying the impact of environmental regulations on carbon emission efficiency that
48. will help to strengthen the role of ER in promoting low-carbon transformation. (3)
49. The study supports improvement in the effectiveness of ER implementation, and is
50. therefore of great significance for improving a country's governance system and
51. capabilities in the field of ecological civilization for critical infrastructure.
52. The rest of the article is organized as follows: Section 2 presents the literature
53. review; Section 3 provides the research methods and data; Section 4 provides the
54. empirical results; Section 5 is the discussions and policy recommendations; and
55. Section 6 finishes with the conclusion and proposed further research.

# 2 Literature review

## 2.1 Carbon emission efficiency measurement

1. Carbon emissions efficiency refers to the efficiency of production activities that
2. generate a corresponding output while inducing carbon dioxide emissions. Carbon
3. emissions efficiency (CEE) is generally divided into two types: static and dynamic.
4. Compared to static CEE, dynamic CEE reflects changes of efficiency over time. This
5. provides a clearer reference for formulating improved low-carbon transformation
6. policies.
7. In recent years, Carbon emissions efficiency (CEE) has attracted significant
8. attention in the research literature. However, a single unified definition of CEE does
9. not yet exist. Mielnik and Goldemberg (1999) applied the ratio of CO2 emissions to
10. energy consumption to represent CEE, but named it the carbon index. The carbon
11. index is now an important measure of a country's energy efficiency (Ang, 1999).
12. However, both carbon productivity and the carbon index are measured by the ratio of
13. CO2 emissions to a single variable, ignoring the effect of the many other confounding
14. variables, such as the economic development level, industrial structure, and factor
15. substitution (Zhou et al., 2010).
16. In order to compensate for this oversimplification, some studies have proposed a
17. multi-dimensional concept of carbon emissions efficiency, that is, when calculating
18. the production technology efficiency, the undesired output of CO2 emissions is
19. included in the evaluation index system. That is why in this research study, we will
20. consider CEE within a comprehensive multi-dimensional index, referring to a
21. technical efficiency that takes CO2 emissions into account.
22. Regarding CEE in the transportation industry, most studies have focused on
23. comparative performance analyses of different types of transportation or geographical
24. regions. Chang et al. (2013) analyzed the provincial CEE of China’s transportation
25. system in 2009 using a slacks-based measure (SBM) model. Wang and He (2017)
26. calculated the marginal abatement cost of CO2 emissions and analyzed the CEE of
27. China’s regional transportation sectors in the 2007–2012 period. They found a
28. negative correlation between CEE and its marginal abatement cost.
29. On the other hand, it can be observed that Data Envelopment Analysis (DEA)
30. has become the mainstream method for carbon emissions efficiency research. Zofı́O
31. and Prieto (2001) used the DEA method to perform a comparative analysis of OECD
32. countries based on their respective carbon emission efficiencies. Choi et al. (2012)
33. estimated carbon emissions reduction costs with a SBM model. Gómez-Calvet et al.
34. (2014) also applied the slacks-based measure (SBM) method to investigate and
35. measure the CEE of EU (European Union) countries. To reduce the subjectivity and
36. deviations of SBM, Sueyoshi et al. (2010) extended the study of Cooper et al. (2000),
37. and proposed a Range Adjusted Measure model that considered undesirable outputs,
38. which avoids setting any parameters subjectively. As a result, this approach improved
39. the objectivity and accuracy of CEE measurement.
40. Oh (2010) proposed a Global Malmquist-Luenberger productivity index, which
41. solved the problem of infeasible solutions. Later, Emrouznejad and Yang (2016)
42. combined a Range Adjusted Measures model with the Global Malmquist-Luenberger
43. productivity index. The new RAM-based global Malmquist-Luenberger productivity
44. index handles undesirable variable outputs and slacks, while is also able to capture
45. dynamic changes in CEE. Since these developments, the index has been considered as
46. a reliable method for measuring dynamic CEE.

## 2.2 Influencing factors of carbon emissions efficiency

1. Recently, more scholars have carried out research on the factors affecting carbon
2. emission efficiency from varied perspectives. Most studies have considered factors
3. such as population, economy, industrial structure, and energy structure. Wang and
4. Wang (2020) studied the influencing factors of short-term and long-term carbon
5. emissions and found that energy efficiency and trade openness are the main factors
6. affecting carbon emissions. They did not only studied the impact of urbanization on
7. carbon emissions efficiency, but also discussed the impact of economic development
8. levels, industrial structure, energy consumption structure, foreign trade and
9. government intervention. Furthermore, Sheng et al. (2020) studied the long-term and
10. short-term effects of economic growth on carbon emissions efficiency, and found that
11. economic growth can improve carbon emissions reduction efficiency. Shen et al.
12. (2019) examined the impact of industrial development levels, foreign trade levels and
13. geographic location on carbon emission efficiency.
14. There are also scholars conducting research on different types of traffic and
15. industries. The study of Wang et al. (2011) concluded that the main factors affecting
16. the CEE of China’s cargo transportation sector were the regional economic and
17. industrial development level, energy utilization efficiency, as well as the number and
18. size of cargo transportation enterprises. Zhou et al. (2019b) found that technological
19. progress and energy structure can improve the carbon emissions efficiency of the
20. construction industry, and the impacts are different in different industries. Moreover,
21. environmental regulations have gradually become one of the important influencing
22. factors in scholars' research. For example, Pan et al. (2019) examined the impact of
23. China's environmental regulations on carbon emissions efficiency. Pei et al. (2019)
24. used a threshold regression model to test the nonlinear relationship between

environmental regulations and carbon emissions.

## 2.3 Impact of environmental regulations on carbon emission efficiency

1. Environmental regulations (ER) are policies adopted by the government to
2. reduce environmental externalities, with the goal of enabling environmental
3. protection and sustainable economic development. Porter (1991) was among the first
4. to propose that appropriate ER could promote technological innovation and improve
5. resource utilization – resulting in the eventual improvement of technical efficiency.
6. This is called the *Porter Hypothesis*. In order to test the Porter Hypothesis, scholars
7. have conducted several empirical studies based on different assumptions, population
8. samples, analysis methods, and selection of different variables (Lanjouw and Mody,
9. 1996, Jaffe and Palmer, 1997, Gray, 1987).
10. However, current research on the Porter effect can be classified as possessing
11. one of two opposing views. Jaffe and Palmer (1997) as well as Brunnermeier and
12. Cohen (2003) support Porter's hypothesis and believe that environmental regulations
13. have a positive impact on industrial technical efficiency; Whereas Gray (1987) and
14. others support the opposite. Hence, despite more research being developed, there still
15. is no definitive answer. Lanoie et al. (2008) analyzed the impact of ER on the
16. productivity of the manufacturing industry in Canada, finding short-term vs.
17. long-term inconsistencies. Alpay et al. (2002) analyzed the impact of ER on the
18. productivity of the food industry in the United States and Mexico during the period
19. 1971-1994, and found clear differences between the two countries in regard to
20. adopting the same ER. Wang et al. (2019) used a threshold model to analyze the
21. nonlinear relationship between environmental regulations and carbon emissions. The
22. study investigated the case of 30 provinces in China and found that ER exhibits a
23. threshold effect on CO2 emissions that is accompanied with significant differences
24. among the eastern, central, and western regions of the country.
25. Regarding the impact of ER on CEE, Pei et al. (2019) examined the provincial
26. panel data of energy-intensive industries for the period 2005-2015 in order to assess
27. the impact of ER on CEE, finding that ER can *directly* improve CEE. However, they
28. also found that ER can also *indirectly* improve the CEE by improving the technical
29. efficiency of the industry. Furthermore, Zhao et al. (2015) found that different types
30. of environmental regulations have different effects on efficiency and carbon emissions.
31. In this case, command and control as well as government subsidies improve
32. efficiency and reduce carbon dioxide, whereas market incentives appear to have little
33. influence. More recently, Zhang et al. (2018) adopted a three-stage DEA method to
34. evaluate the CEE of the construction industry in China, finding that there is a
35. threshold effect of ER.

## 2.4 Knowledge gap

1. From the developed literature review, there are three limitations in previous
2. studies:
3. (1) The current research on carbon emission efficiency mostly focuses on the
4. static perspective, and many of the existing studies ignore the differences in
5. production frontiers in different periods. There are relatively few dynamic studies on
6. carbon emissions efficiency.
7. (2) Carbon emissions efficiency with multi-dimensional characteristics has now
8. become the focus of research, but most of the existing studies focus on the automotive
9. industry as well as the impact of factors such as population, economy, industrial
10. structure, and energy structure. Few studies have focused on the effect of
11. environmental regulations on carbon emissions efficiency of transportation
12. infrastructure.
13. (3) There are currently different (opposing) opinions on the impact of
14. environmental regulations on carbon emissions efficiency. Some empirical studies
15. that are based on a single perspective are single-sided, and it is therefore necessary to
16. analyze the impact of environmental regulations on carbon emissions efficiency from
17. multiple perspectives (such as the threshold effect, etc.).

# 3 Research methods

## 3.1 RAM-based global Malmquist-Luenberger productivity index (GML)

1. GML can effectively deal with undesired output and slack variables, while
2. avoiding the use of subjective model parameters. This numerical approach improves
3. the accuracy and comparability of efficiency measurement results. Hence, this study
4. combines the RAM model with the global Malmquist-Luenberger production index to
5. construct a RAM-based global Malmquist-Luenberger productivity index (GML).
6. This enhanced model will be used to measure the dynamic efficiency of China’s
7. transportation infrastructure carbon emissions from 2001 to 2017, thereby accurately
8. reflecting the variation of carbon emissions efficiency in the 17-year period of
9. analysis.
10. In this study, the transportation infrastructure of each Chinese province is
11. supposed as a Decision-Making Unit (DMU) and is represented as DMUj (j = 1,2,3 ...
12. n) assuming that in time period (t = 1,2,3 ... T) each DMU requires *m* inputs and
13. produces *s* desirable outputs and *k* undesirable outputs. These are respectively noted

219 as I = (i1, i2, … , im) ∈ R+ , O = (o1, o2, … , os) ∈ R+ and

m×n

s×n

1. UO = (uo1, uo2, … , uok) ∈ R+ . Based on these assumptions, the production

k×n

1. function is:

Pt = {(Ot, UOt): I tcan produce(Ot, UOt)}

I ∈ R+ ，O ∈ R+ , ，UO ∈ R+

(1)

m×n

s×n

k×n

1. However, this study aims to measure the CEE of transportation infrastructure
2. from the perspective of total factor productivity (TFP). To overcome the problem of
3. aggregation of inputs and outputs, a DEA model is therefore needed. As shown in the
4. literature review, a RAM model does not involve subjectivity when setting the model
5. parameters (Wang and Yuan, 2020). Hence, following the approach of (Sueyoshi et al.,
6. 2010), a RAM model considering undesirable output can be constructed as follows:

min0 = 1 − (RtTdt + RtTdt + +RtT dt ) (2)

I I 0 0 u0 u0

∑n }.jlt + dt = lt

j=1 j I O

∑n }.jOt − dt = Ot

s. t.

j=1 j 0 O

∑n }.jUOt + dt = UOt

j=1 j u0 O

l∑n

}.j = 1, dt, dt , dt , }.j ≥ 0

where:

j=1

I 0 u0

RtT = (R1t, R2t, … , Rmt)T

I I I I

RtT = (R1t, R2t, … , Rst)T

0 0 0 0

229 RtT = (R1t , R2t , … , Rkt )T (3)

u0 u0 u0 u0

230 In equation (2), }.j is the combination coefficient of each input and output

231

variable of a DMUj. When }.j satisfies the condition ∑n

}.j = 1, the RAM model is

232 under the assumption of variable returns to scale (VRS). When the constraint of

j=1

∑

233

n j=1

}.j = 1 is removed, the RAM model turns into being under the assumption of

1. constant returns to scale (CRS). dt , dt and dt represent the slack of input,

I 0 u0

1. desirable output, and undesired output respectively, and reflect the degree of input
2. redundancy and output shortage. Meanwhile, 0 is static CEE measured from the
3. perspective of TFP. This variable always satisfies 0 ≤ 1.
4. However, evaluating CEE solely with a RAM model may have the following
5. problems: (a) the calculation would be very complex; (b) it would be impossible to
6. analyze the spatial and temporal changes of CEE. To overcome these problems, this
7. study combined the RAM model with a global Malmquist-Luenberger productivity
8. index (GML) as shown below:

→G (It+1, Ot+1, UOt+1) MLPG(It, Ot, UOt, It+1, Ot+1, UOt+1) = D DDF

→G (It, Ot, UOt)

D DDF

→G (Ip, Op, UOp) = minθ = 1 − (RpTdp + RpTdp + RpT dp )

D DDF

I I 0 0

u0 u0

∑T ∑n AjtIt+dp=Ip

t=l j=l j

∑T ∑n Ajt0t-dp =0p

s. t.

t=l j=l j 0

(4)

∑T ∑n Ajtu0t+dp =u0p

t=l

j=l

j u0

Ajt�O,j=1,..,n;t=1,..,T

1. where:

RtT = (R1t, R2t, … , Rmt)T

I I I I

RtT = (R1t, R2t, … , Rst)T

0 0 0 0

245 RtT = (R1t , R2t , … , Rkt )T (5)

u0 u0 u0 u0

246

In equation 4, MLPG represents dynamic CEE.

→G is the Directional

D DDF,V

247

Distance Function (DDF) under the assumption of VRS, and

→G represents the

D DDF,C

1. DDF under the assumption of CRS. In particular, under the assumption of VRS,
2. MLPG can be decomposed as:

MLPG(It, Ot, UOt, It+1, Ot+1, UOt+1)

V

PTEt+1

t

BPGt,t+1 SEt+1(It+1, Ot+1, UOt+1)

= PTEt

× [ t+1 ] × ( BPGt,t+1

SEt(It, Ot, UOt) ) =

= PECt,t+1 × BPCt,t+1 × SCHt,t+1 (6)

→G (It,0t,u0t) t( t t) DDDF,C

→G (It,0t,u0t)

SE I , O =

DDDF,V

where PTEt represents Pure Technical Efficiency at time t, while PECt,t+1

represents the change of PTE between time t and t + 1. Additionally, BPGt，t+1

t

(7)

1. represents the Best Practice Gap between the contemporaneous technology frontier
2. and global technology frontier. Accordingly, to measure the technological changes
3. between the t and t + 1 periods, we use BPCt，t+1 to denote the change in BPG.
4. Meanwhile, SCHt,t+1 denotes the ratio of two scale efficiencies for the two
5. periods under the global benchmark technology.

## 3.2 Hansen’s panel threshold model

1. Hansen’s panel threshold model is introduced to analyze the threshold effect.
2. This model can identify the limit values of independent variables that can cause a
3. turning point in the dependent variable. These thresholds, of course, depend on the
4. data characteristics and reveal the influence of independent variables on the explained
5. variable by partition (Ji et al., 2019). Therefore, Hansen’s panel threshold model
6. avoids the subjectivity and arbitrariness of artificial classification, improving the
7. accuracy of the regression model results. The general form of Hansen’s panel
8. threshold model is:
9. yit = ui + xitf31 ∙ l(qit ≤ y) + xitf32 ∙ l(qit > y) + 0X + Eit (9)
10. where i represents the DMU and *t* represents the year, whereas f31, f32, and 0 are
11. corresponding estimated coefficients. yit, xit, and qit are the explained variable,
12. independent variables and threshold variable respectively. Additionally, y is the
13. threshold value, ***X*** is a set of control variables, and Eit is the random error. l(∙) is
14. the index function, and l(∙)=1, when the condition in parentheses is satisfied,
15. otherwise l(∙)=0. The panel data is partitioned according to the threshold variable qit
16. and the threshold value γ.
17. However, equation (9) represents a single threshold model. Based on this, a
18. double threshold model and a triple threshold model can also be built as follows:

yit = ui + xitf31 ∙ l(qit ≤ y1) + xitf32 ∙ l(y1 < qit ≤ y2)

278 +xitf33 ∙ l(qit > y2) + 0x + Eit (10)

yit = ui + xitf31 ∙ l(qit ≤ y1) + xitf32 ∙ l(y1 < qit ≤ y2)

279 +xitf33 ∙ l(y2 < qit ≤ y3)+xitf34 ∙ l(qit > y3) + 0x + Eit (11)

1. respectively. Here, the single threshold, double threshold, and triple threshold models
2. are applied progressively to test the potential threshold effects.

## 3.3 Data

1. This study selects panel data from 2001 to 2017 in 30 provinces of China, except
2. Hong Kong, Macau, Taiwan and Tibet because the data from these regions was not
3. readily available. The panel data used in this study come from *China’s Statistical*
4. *Yearbook (2001-2018)* and *China’s Energy Statistical Yearbook (2001-2018)*.

## 3.3.1 Carbon emissions efficiency evaluation indicator system

1. (1) Input indicators
2. This research study uses an index system supported in the existing research
3. literature on index selection. For further details of the specific index system employed,
4. see Table A-3 in Appendix A. The inputs of transportation infrastructure mostly
5. comprise labor, capital, and energy. In general, labor input is measured by laboring
6. hours. However, due to the lack of relevant statistical data, we used the number of
7. engaged persons in the transportation industry to represent labor input. Based on the
8. investment in fixed assets, transportation industry capital was calculated by the
9. perpetual inventory method. Details of the calculations are shown in Appendix B of
10. the *Supplemental Material*. As for the energy input, eight primary energy
11. consumptions were selected: raw coal, coke, gasoline, kerosene, diesel, fuel oil,
12. liquified petroleum gas, and natural gas. These were then converted to their standard

coal equivalent as shown in the Table A-1 of Appendix A.

1. (2) Desirable output indicators
2. In general, desirable outputs of transportation infrastructure mainly comprise two
3. components, namely economic value and practical value. This study used the added
4. value of the industry to represent economic value. Meanwhile, practical value was
5. represented by cargo turnover and passenger turnover as in the study of (Liu et al.,

2017).

1. (3) Undesirable output indicators
2. As mentioned earlier, we evaluated CEE from the perspective of TFP. Therefore,
3. the undesirable output of transportation infrastructure is represented by CO2 emissions.
4. The carbon emissions coefficient method was adopted for the calculation as
5. recommended by the United Nations Intergovernmental Panel on Climate Change
6. (IPCC) (IPCC, 2006). The specific equation is as follows:

CO2 = ∑n

Ei × NCVi × CEFi × COFi × (44) (12)

12

i=1

1. where Ei and NCVi represent the terminal consumption and net calorific value of the
2. ith energy respectively, CEFi and COFi represent the carbon emissions factor and
3. carbon oxidation ratio, 44/12 corresponds to the coefficient of carbon conversion, and
4. the CO2 emissions of each energy source can be calculated as in Table A-2 of

Appendix A.

## 3.3.2 Explained variable

1. The explained variable is the CEE of the transportation infrastructure as
2. measured by a RAM-based global Malmquist-Luenberger productivity index (GML).

As shown earlier, this index is noted as GML.

## 3.3.3 Independent variable and threshold variable

1. ER is the independent variable in the Hansen’s panel threshold model and ER is
2. also the threshold variable adopted in this approach. The content of ER is complex,
3. and not only includes the environmental laws and policies implemented nationwide,
4. but also some regional or industrial regulations. All of these regulations may affect
5. CEE. In order to fully reflect the role of ER, by referring to previous studies, the
6. ratio of the total input of environmental governance to the GDP of each province was
7. selected. This characterizes the intensity of ER from an overall perspective (Zhang et

al., 2018).

## 3.3.4 Control variables

1. The control variables comprise the regional economic development level,
2. technology innovation level, institutional factor, and opening-up level.
3. Previous studies identified a relationship between regional economic
4. development level and regional industry development (Zheng and Wang, 2019b). In
5. general, high economic development levels can lead to upgrades of industrial
6. structure, thereby optimizing resources allocation and increasing industry TFP (Zhou
7. et al., 2019c). The natural logarithm of per capita GDP of each province was selected
8. to represent the regional economic development level, which is expressed as
9. LnECO.
10. Improvement of the technology innovation level helps to improve the
11. companies’ resource utilization efficiency and reduce environmental pollution (Luo
12. et al., 2019). The technology innovation level may also have an impact on CEE.
13. (Quazi and Talukder, 2011) found a significant positive correlation between regional
14. technology innovation level and its educational level. Therefore, regional higher
15. education proportion of each province was selected to represent its technology
16. innovation level – hereinafter denoted as RES.
17. Previous studies also found that the regional opening-up level has a significant
18. impact on the transportation industry’s TFP (Chu et al., 2014). On the one hand, an
19. environment conducive for foreign direct investment (FDI) would promote the
20. introduction of technology and human resources. This could contribute to improving
21. technical efficiency. On the other hand, transportation infrastructure is highly
22. dependent on investment. Hence, the introduction of foreign investment may also
23. potentially cause an increase of CO2 emissions, leading to a decrease in CEE. Here,
24. the natural logarithm of regional FDI is used to represent the opening-up level,
25. expressed by LnOPEN.
26. The institutional factor is regarded as an important factor influencing industrial
27. development. Currently, China has encouraged the participation of social capital in
28. transportation infrastructure construction, despite the government still being the major
29. investor (Ren et al., 2011). In general, greater regional government investment means
30. lower regional marketization. This may lead to a lack of motivation for the
31. introduction of new technologies, materials, and energy. Of course, not all of these are
32. conducive to reducing carbon emissions. Hence, the ratio of state-owned assets to the
33. whole society's specified asset investment in the transportation industry, expressed as
34. OW, was selected to represent the institutional factor. The descriptive statistical
35. results of all the above variables are shown in Table 1.
36. Table 1. The descriptive statistical of all variables.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | Variables | Sample size | Min | Max | Mean | SD |
| CEE | 480 | 0.779 | 1.201 | 0.993 | 0.031 |
| ER | 480 | 0.3 | 4.24 | 1.325 | 0.672 |
| LnECO | 480 | 8.056 | 11.768 | 10.156 | 0.774 |
| RES | 480 | 0.018 | 0.476 | 0.01 | 0.066 |
| OW | 480 | 0.101 | 0.658 | 0.323 | 0.117 |
| LnOPEN | 480 | 7.31 | 15.096 | 12.21 | 1.779 |
| 374 |  |  |  |  |  |  |

# 4 Results

## 4.1 Data test for regression analysis

1. In order to ensure the accuracy of the regression analysis, panel unit root tests
2. and panel co-integration tests were used to characterize the panel data. Details of

these two methods are provided in Appendix C of the Supplemental Material.

1. (1) Panel unit root test
2. The Augmented Dickey-Fuller (ADF) test was used to determine whether the
3. panel data of each variable had a unit root. Then, the Phillips-Perron (PP) test and
4. Im–Pesaran–Shin (IPS) test were used to verify the results. As shown in Table 1, the
5. results of the three methods are highly consistent. This means the null hypothesis of
6. the existence of unit root is strongly rejected, indicating that all variables are

stationary.

1. Table 2. Results of the panel unit root test.

|  |  |  |  |
| --- | --- | --- | --- |
|  | ADF test | PP test | IPS test |
| Variable | Z statistic | Z statistic | W statistic |
|  | (p value) | (p value) | (p value) |
| GML | -4.62753\*\*\*  (0.00060) | -14.53050\*\*\*  (0.0000) | -4.18153\*\*\*  (0.0000) |
| ER | -1.69712\*\* | -3.23160\*\*\* | -1.55785\* |

(0.0448) (0.0006) (0.0596)

Ln ECO

-5.79856\*\*\* (0.0000)

-8.09060\*\*\* (0.0000)

-5.53524\*\*\* (0.0000)

RES

-7.17679\*\*\* (0.0000)

-2.45952\*\*\* (0.0070)

-6.89297\*\*\* (0.0000)

-1.67012\*\*

OW

(0.0474)

-4.92068\*\*\* (0.0000)

-1.82117\*\* (0.0343)

Ln OPEN

-5.23641\*\*\* (0.0000)

-3.46886\*\*\* (0.0003)

-7.62693\*\*\* (0.0000)

1. Note: \*\*\*, \*\*, and \* represent statistically significant at the 1%, 5%, and 10% levels
2. respectively.
3. (2) Panel co-integration test
4. After the panel unit root test, the Kao panel co-integration test was used to
5. investigate the co-integration relationship of each variable. As shown in Table 2, the
6. T statistic value was -1.406589 and the p value 0.0000. This means there is a
7. long-term co-integration relationship between the variables, and that regression tests

can be directly performed on the panel data.

1. Table 3. Panel co-integration test results.

ADF

T statistic p value

-12.43575\*\*\* 0.0000

|  |  |  |
| --- | --- | --- |
| Residuals | 0.002481 | - |
| HAC variance | 0.000575 | - |

1. Note: \*\*\*indicates statistically significant at the 1% level.

## 4.2 Dynamic carbon emissions efficiency analysis

1. Analysis of the carbon emissions efficiency of the transportation infrastructure
2. was carried out at two levels, namely the national level and the regional level. At the
3. national level, the data of all 30 provinces are used for analysis; at the regional level,
4. the 30 provinces are divided into three regions: east, middle and west, and the carbon
5. emissions efficiency in the three regions is analyzed in each of them.

## 4.2.1 National level

1. For further details on the dynamic efficiency and decomposition of carbon
2. emissions from transportation infrastructure at the national level go to Table A-4 in
3. Appendix A.
4. From 2001 to 2017, the CEE of the transportation infrastructure showed a
5. declining-rising-declining trend. Based on this trend, the observation period was
6. further divided into three stages as follows: 2001-2006, 2007-2012, and 2013-2017.
7. These periods are represented in different figures later. Due to the long observation
8. period, if the GML and its decomposition are accumulated and rebased on the year
9. 2001, it would be difficult to observe variations in each stage. Therefore, we set the
10. starting year of each of the three stages as the base year for comparison.
11. As shown in Figure 1, in time period 2001-2016, GML decreased year by year
12. with an average annual decline of 1% and a cumulative decline of approximately
13. 4.93%. From the decomposition of the GML, the average annual decline rates of
14. PEC (changes in technological efficiency), BPC (technological change), and SCH
15. (change in scale efficiency) were 0.06%, 0.83%, and 0.41% respectively. This is due
16. to the low level of technological innovation in the field of transportation
17. infrastructure during the period. It may also have to do with an insufficient
18. utilization of new energy sources, which could not effectively promote technological

**Efficiency value**

progress.



1.020

1.000

1.000

1.001

0.998

0.995

0.993

1.004

0.998

1.003

0.993

1.001

0.997

0.988

0.980

0.976

0.976

0.980

0.960

0.940

GML PEC BPC SCH

2001

0.977

0.975

0.957

0.959

0.951

2002

2003

**Year**

2004

0.953

2005

2006

Figure 1. GML and its decomposition during 2001-2006.

1. As shown in Figure 2, during 2007-2012, GML showed an overall growth trend,
2. at an average annual rate of 0.24% and a cumulative increase of approximately
3. 1.43%. This indicates that the CEE improved slightly. From the decomposition of
4. GML, the average annual growth rates of PEC and BPC were 0.03% and 0.13%
5. respectively, which promoted the growth of CEE in this period. The reason for this
6. change may have been that technology advancements in transportation infrastructure
7. led to small productivity improvements. However, during this period, SCH still had
8. an overall declining trend (average annual decline of 0.64% and cumulative decrease
9. of about 3.60%). The deterioration of economies of scale is the main reason for
10. limiting the further growth of carbon emissions efficiency during this period, and

**Efficiency value**

resource allocation still needs to be improved.



1.040

1.020

1.019

1.000

1.009

1.001

1.006

1.005

1.000

0.993

0.999

0.989

1.006

1.003

0.992

1.014

1.008

1.001

0.980

0.997

0.985

0.968

1.003

0.992

0.960

GML

PEC

BPC SCH

0.988

0.982

0.961

0.964

0.947

0.940

2006

2007

2008

2009

**Year**

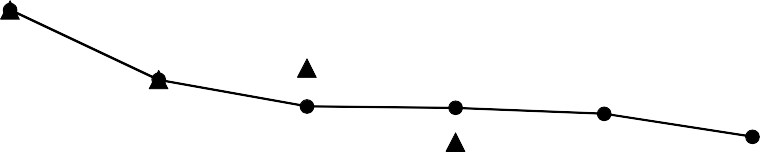
2010

2011

2012

Figure 2. GML and its decomposition during 2007-2012.

1. As shown in Figure 3, GML sharply declined during 2013-2017, with an
2. average annual decrease rate of 1.48%. This highlights that the carbon emissions
3. efficiency of China's transportation infrastructure has dropped significantly. From the
4. decomposition results, BPC and SCH also decreased significantly (average annual
5. declination rates of 1.6% and 1.14% respectively). The significant decline in BPC
6. means that the technological frontier in the same period is approaching the global
7. technological frontier. This along the direction of more carbon dioxide emissions and
8. less expected output. Furthermore, the expected output of cargo turnover and
9. passenger turnover have both declined to a certain extent. Meanwhile, PEC
10. continued growing, although only modestly, with its improvement unable to
11. compensate for the decrease in BPC and SCH.



1.040

1.002

1.018

1.000

1.000

0.960

0.987

0.969

0.969

0.956

0.987

0.974

0.959

0.957

1.010

0.920

GML PEC BPC SCH

0.957

0.942

0.941

0.954

0.931

0.918

0.944

0.928

0.922

0.880

2012

2013

2014

**Year**

2015

2016

2017

**Efficiency value**

1. Figure 3. GML and its decomposition during 2013-2017.

## 4.2.2 Regional level

1. This research study also analyzed the dynamic efficiency of carbon emissions
2. of transportation infrastructure and its decomposition at the overall national level. In
3. order to analyze the spatial distribution of carbon emissions efficiency, we follow Bi
4. et al. (2014) approach and group the 30 Chinese provinces by similar geographical
5. location and level of economic development. That resulted in three regions of
6. analysis, i.e., East, Middle and West. The partition in the three regions is listed in

Table 4.

Table 4. Three regions in China.

|  |  |  |
| --- | --- | --- |
| East | Middle | West |
| Liaoning, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian,  Guangdong, Hainan | Heilongjiang, Jilin, Shanxi, Henan, Hubei, Anhui, Hunan, Jiangxi | Inner Mongolia, Xinjiang, Ningxia, Qinghai, Gansu, Shaanxi, Sichuan, Chongqing,  Guizhou, Yunnan, Guangxi |

1. As shown in Figure 4, the GML of the three regions also had an approximate
2. declining-rising-declining trend during the period 2001-2017. However, the GML
3. values among the three regions were clearly imbalanced. During the observation
4. period, the GML value of the East region was always greater than the Middle and
5. West regions. Similar to the results of Ren et al. (2018) and Bi et al. (2014), it can
6. also be observed that the differences in regional economic development levels and
7. the level of optimization of industrial structure are the major reasons for this
8. inequality.
9. As shown in Figure 5, there also were clear differences in the PEC (pure
10. technical efficiency) values of the three regions (i.e. values for East > Middle >
11. West regions). In general, PEC had an overall increasing trend in the second and
12. third stages. However, in the first stage, the PEC of the East and Middle regions
13. had an increasing trend, while the West region and the overall country experienced
14. a downward trend. The level of R&D resource allocation in the East region is
15. significantly higher than in the central and western regions. This higher resource
16. allocation provided a more favorable environment for technological progress in the
17. East region.
18. As shown in Figure 6, the BPC of the three regions kept deceasing from 2001 to
19. 2017. This indicates that the contemporaneous production frontier shifted towards
20. the global production frontier (i.e., producing less desirable outputs and more CO2
21. emissions). This also means that reducing CO2 emissions to improve the current
22. production frontier is a shared challenge for the three regions alike.
23. As shown in Figure 7, the SCH of the three regions had a continuous downward
24. trend. This indicates that the scale efficiency of all regions deteriorated during
25. 2001-2017. It also shows that the optimization of the regional resources allocation is
26. a pressing need to curb the decline of economies of scale in China. Yet, there are
27. obvious differences between the three regions, as the East region’s SCH deteriorated
28. much more. This deterioration of the East economies may have been caused by the

excessive concentration of resources in this Chinese region.

**Efficiency value**



1.100

The first stage

The second stage

The third stage

1.050

1.000

0.950

0.900

Nation East region

Middle region

West region

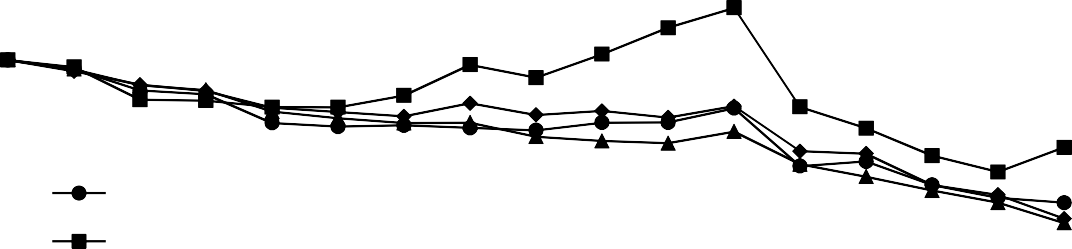
0.850

2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

**Year**

**Efficiency value**

Figure 4. GML of nation and three regions from 2001 to 2017.



1.100

The first stage

The second stage

The third stage

1.050

1.000

0.950

0.900

0.850

0.800

Nation East region

Middle region

West region

0.750

2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

**Year**

1. Figure 5. PEC of nation and three regions from 2001 to 2017.



1.050

The first stage

The second stage

The third stage

1.000

0.950

0.900

Nation

0.850 East Region Middle region

0.800

West Region

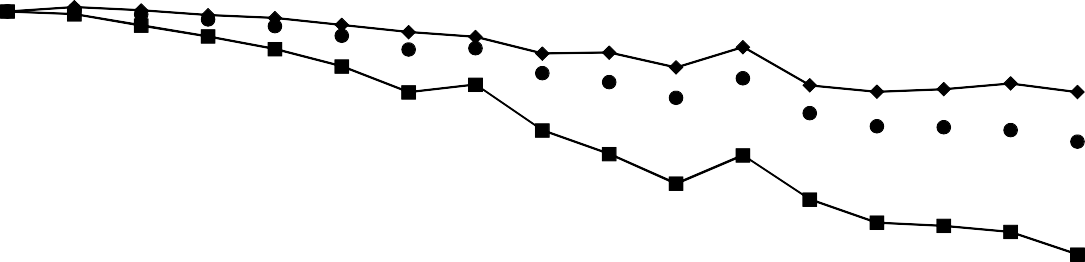
0.750

2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

**Year**

**Efficiency value**

1. Figure 6. BPC of nation and three regions from 2001 to 2017.



1.100

The first stage

The second stage

The third stage

1.000

0.900

0.800

Nation

East region

Middle region West region

0.700

2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017

**Year**

**Efficiency value**

1. Figure 7. SCH of nation and three regions from 2001 to 2017

## 4.3 Analysis of the threshold effect

1. According to the regression analyses above, environmental regulations (ER)
2. have both positive and negative effects on carbon emissions efficiency (CEE).
3. However, ER may have a nonlinear effect on CEE when the threshold model is used

514 (Lu and Li, 2020).

1. This research study uses the Tobit regression model to test the impact of ER on
2. CEE before the threshold regression. Considering the existence of omitted variables
3. and endogenous problems, the Tobit regression model with fixed effects and random
4. effects was selected. Results are given in Appendix C of the *Supplemental Material*.
5. Namely, Hansen’s panel threshold model was applied to analyze the threshold
6. effect of environmental regulation (ER) on carbon emissions efficiency (CEE) for the
7. transportation infrastructure. Calculations were performed with StataMP 13. As
8. shown in Table 5, only the test for the single threshold F was significant with a
9. bootstrap p value of 0.003. Therefore, there is a single threshold effect of ER on CEE
10. in the East region corresponding (0.540). This means there is a nonlinear effect of ER

on CEE in this region.

1. Table 5. Test for threshold effects in the East region.

Threshold

Threshold

Critical values

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Region |  |  | F value | p value |  | | |
|  | model | value |  |  | 1% | 5% | 10% |
|  | Single | 0.540 | 20.092\*\*\* | 0.003 | 15.158 | 8.156 | 5.895 |
| East region | Double | - | 1.952 | 0.220 | 8.186 | 4.483 | 3.297 |
|  | Triple | - | 2.382 | 0.113 | 6.784 | 4.273 | 2.527 |

1. Note: \*\*\* means significant at 1%.
2. As shown in Table 6, by comparing the significance levels, it is more likely to
3. find a single or double threshold effect of ER on CEE in the Middle region. However,
4. according to the maximum likelihood graph of the double threshold model in Figure
5. 8, the second threshold value is difficult to identify. Hence, we consider that the

single threshold model is representative enough with a threshold value of 0.870.

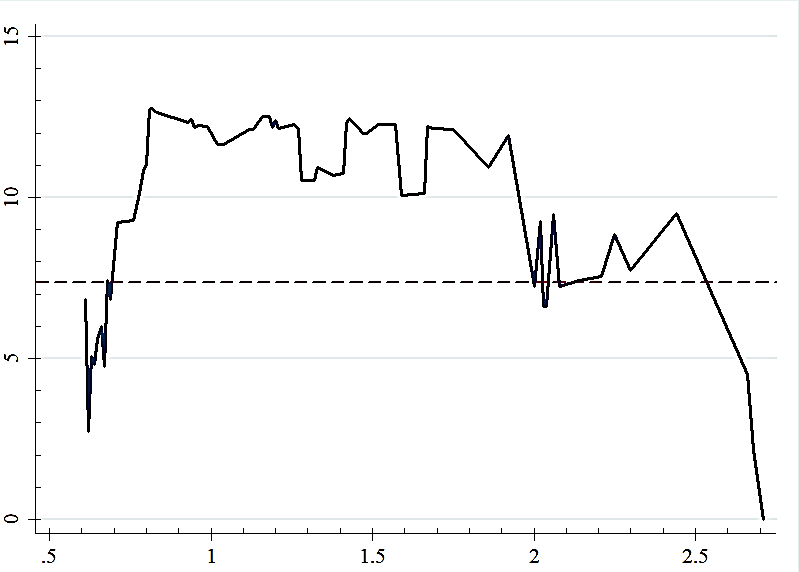
1. Table 6. Test for threshold effects in middle region.

Threshold

Threshold

Critical values

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Region | model | value | F value | p value | 1% | 5% | 10% |
|  | Single | 0.870 | 18.825\*\*\* | 0.003 | 9.955 | 6.691 | 4.589 |
| Middle | Double | 2.060 | 3.238\*\*\* | 0.000 | 0.121 | -4.674 | -6.729 |
| region |  | 2.710 |  |  |  |  |  |
|  | Triple | - | 7.793 | 0.040 | 9.511 | 7.138 | 4.873 |

1. Note: \*\*\* means significant at 1%.
2. 
3. Figure 8. Maximum likelihood graph of the second threshold value in the double

threshold model for the Middle region.

1. As shown in Table 7, only the test for the double threshold model was strongly
2. significant with a bootstrap p value of 0.037 (threshold values of 0.820 and 0.890).

This means that there is a nonlinear effect of ER on CEE in the West region.

1. Table 7. Test for threshold effects in the West region.

Threshold

Threshold

Critical value

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Region | model | value | F value | p value | 1% | 5% | 10% |
|  | Single | - | 1.747 | 0.277 | 9.105 | 5.486 | 3.543 |
|  |  | 0.820\*\* |  |  |  |  |  |
| West region | Double | 0.890\*\* | 7.197\*\* | 0.037 | 10.860 | 5.199 | 3.878 |
|  | Triple | - | 2.887 | 0.150 | 8.180 | 4.657 | 3.763 |

1. Note: \*\* means significant at the 5% level.
2. After the most suitable threshold models in each region were identified, they
3. were applied to perform a regression analysis to estimate the ER’s coefficient. The
4. regression results are shown in Table 8. The first is the East region. When ER is less
5. than 0.540, for a 1% increase in ER, the positive impact on CEE increases by
6. 0.1810%, and the impact is significant. When ER is greater than 0.540, this positive
7. effect increases by only 0.0065%, and the decrease rate is 96.2%. In the Middle
8. region, the situation is similar to the East region. The difference is that, when ER in
9. the Middle region is above the threshold value (ER = 0.870), the ER’s coefficient
10. decreases by 60.3% despite the significance level remaining the same. As for the
11. West region, when ER remains within the range of 0.820 to 0.890, the increase of ER
12. can cause a significant negative effect on CEE. 561
13. Table 8. Regression results of the corresponding threshold model in three
14. regions.

Region Threshold

Coefficient Std.

p 95% confidence interval



|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | variable |  | Deviation | value |  | |
|  | ER<0.540 | 0.181\*\*\* | 0.045 | 0.000 | 0.093 | 0.269 |
| East | ER≥0.540 | 0.006 | 0.01 | 0.500 | -0.012 | 0.025 |
| region | LnECO | -0.022 | .0162 | 0.183 | -0.054 | 0.01 |
|  | RES | -0.044 | 0.138 | 0.753 | -0.316 | 0.229 |
|  | OW | 0.009 | 0.087 | 0.922 | -0.162 | 0.179 |
|  | LnOPEN | 0.027\*\*\* | 0.01 | 0.008 | 0.007 | 0.048 |
|  | \_cons | 0.845\*\*\* | 0.162 | 0.000 | 0.526 | 1.164 |
|  | ER<0.870 | 0.044\*\*\* | 0.01 | 0.000 | 0.024 | 0.063 |
|  | ER≥0.870 | 0.017\*\*\* | 0.005 | 0.001 | 0.007 | 0.028 |
| Middle | LnECO | 0.005 | 0.01 | 0.602 | -0.014 | 0.025 |
| region | RES | -0.4436\*\*\* | 0.127 | 0.001 | -0.694 | -0.192 |
|  | OW | -0.12\*\*\* | 0.043 | 0.007 | -0.021 | -0.034 |
|  | LnOPEN | -0.007 | 0.005 | 0.132 | -0.017 | 0.002 |







|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | \_cons | 1.075\*\*\* | 0.08 | 0.000 | 0.917 | 1.233 |
|  | ER<0.820 | 0.003 | 0.007 | 0.692 | -0.011 | 0.017 |
|  | 0.820≤ER<0.890 | -0.021\*\*\* | 0.008 | 0.009 | -0.036 | -0.005 |
|  | ER≥0.890 | -0.003 | 0.006 | 0.565 | -0.015 | 0.008 |
| West | LnECO | -0.003 | 0.005 | 0.483 | -0.013 | 0.006 |
| region | RES | -0.067 | 0.075 | 0.375 | -0.216 | 0.082 |
|  | OW | -0.03 | 0.026 | 0.261 | -0.082 | 0.022 |
|  | LnOPEN | 0.003 | 0.002 | 0.123 | -0.001 | 0.006 |
|  | \_cons | 1.016\*\*\* | 0.046 | 0.000 | 0.926 | 1.107 |

1. Note: \*\*\* means significant at 1%.

# 5. Discussion and policy implications

1. At the national level, we have found that the CEE of transportation
2. infrastructure had a declining-rising-declining trend during 2001 to 2017. During
3. 2001-2006, the declining trend was mainly caused by the low level of the pure
4. technical efficiency. Due to the low level of technology innovation in the
5. transportation industry, the low utilization rate of new energy was unable to
6. effectively promote technology progress (Xie et al., 2017). In the period of
7. 2007-2012, CEE grew mainly because of the improvement in pure technical
8. efficiency and the contemporaneous production frontier. In 2006, the Chinese
9. government issued the "*China’s National Plan to address Climate Change*" and
10. thereafter gradually strengthened CO2 emissions control measures. The introduction
11. of these policies had the affect of accelerating technology innovation across various
12. industries, and thereby boosted economic development, as well as the use of new
13. forms of energy, technologies, and materials (Chen et al., 2019). In summary, all
14. these actions further promoted the progress of technology development and
15. innovation. However, in 2013-2017, CEE dropped sharply. This was mainly caused
16. by deterioration of the contemporaneous production frontier and scale efficiency.
17. At the regional level, there were obvious heterogeneities in the CEE of
18. transportation infrastructure and its decomposition. The development of pure
19. technical efficiency of the East region was always at a higher level than that of the
20. Middle and West regions. From a regional economic perspective, industrial
21. development was closely related to the regional economic development level (Zheng
22. and Wang, 2019a). Hence, due to the obvious differences in regional economic
23. development levels across the three regions, it is reasonable to expect that the pure
24. technical efficiency of the East region would have been relatively high. Meanwhile,
25. compared with the East and Middle regions, the West region’s contemporaneous
26. production frontier and scale efficiency evidenced a higher development trend. This
27. was partially the consequence of the support received by the Western Development
28. Plan of China. On implementing this plan, both transportation infrastructure and its
29. energy efficiency improved in the West region significantly (Zhang et al., 2019). It
30. also improved its contemporaneous production frontier. In addition, China’s national
31. level “One Belt and One Road” initiative further promoted the renovation and
32. construction of transportation infrastructure in the West region. This positive effect
33. also relied on economies of scale in the West region (Liu and Xin, 2019) and reduced
34. the deterioration of scale efficiency.
35. The threshold regression results are a key focus area of this study. Overall, akin
36. to the results of Chen et al. (2019) and Ren et al. (2018), environmental regulations
37. seem to have a nonlinear effect on carbon emissions efficiency, and the effects of
38. environmental regulations are different in different regions. In this regard, Zhang et
39. al. (2020) found an inverted U-shaped relationship between China’s environmental
40. regulations and carbon emissions. However, our study has further identified the
41. existence of some threshold effects of environmental regulations (ER) on carbon
42. emissions efficiency. It has found that there is a single threshold in the East and
43. Middle regions, whereas there are double thresholds in the West region. More
44. precisely, we find in the East region that when ER is >0.540, its coefficient becomes
45. much smaller compared to ER<0.540. This means that ER in the East region should
46. be controlled circa 0.540, a point at which it could really achieve the maximum
47. improvement of CEE.
48. At the same time, the control variable LnOPEN is significant and has a positive
49. effect on CEE. This is contrary to the negative effect identified by Ding et al. (2018).
50. Hence, it is shown that the so called "pollution paradise" hypothesis does not hold in
51. the East region. This is due to the high level of economic development and strict
52. environmental regulations in the East region that effectively supervise foreign
53. business activities. Namely, they cause some polluting foreign businesses to invest in
54. other regions with loose ER, thereby improving the CEE of the East region.
55. Similar results were observed in the Middle and West regions. Therefore, for the
56. Middle region, a balanced relationship between investment in environmental
57. pollution control with CEE needs to be explored. Contrary to the result of Ding et al.
58. (2018), the technology innovation level has a significant negative impact on CEE.
59. This phenomenon is caused by conflicting research objectives. The Middle region
60. has a large level of investment in scientific research, but due to the lack of an
61. effective scientific and technological development system, the scientific
62. commercialization rate is low. In addition, state-owned (OW) assets also had a
63. significant negative impact on CEE. The excessive proportion of state-owned assets
64. can easily lead to monopoly problems and reduce the enthusiasm for using new
65. technologies, new materials and new types of energy. Therefore, the Middle region
66. can further support with social capital its participation in transportation infrastructure
67. construction, operation and maintenance to alleviate this negative impact.
68. Also contrary to the result of Ding et al. (2018), this research study shows that
69. there may be an inverted "U" relationship between ER and CEE in the West region.
70. When ER<0.820, CEE generally increases with the increase of ER, and when 0.820
71. ≤ER, CEE decreases significantly with the increase of ER. This highlights that only
72. a moderate level of environmental regulation can promote the progress of green
73. technology. Moreover, when the government interferes excessively, environmental
74. regulations becomes less effective. Consequently, the West region should keep ER
75. below 0.820 as much as possible, and at the same time, pay special attention to the
76. possible negative impact on CEE when enhancing ER.
77. As a result, in order to improve the CEE of transportation infrastructure, the
78. following recommendations are provided for policy makers:
79. *(1) Encourage green technology innovation.* This research study identified that
80. technology progress is the main source of CEE growth for China's transportation
81. infrastructure. Therefore, the government should focus on policy guidance and
82. stimulate the endogenous power of companies as well as stimulating innovative
83. practices. For example, financial subsidies and tax incentives can be granted to
84. industrial companies undertaking green technology innovation. It is also
85. recommended to create channels for the transformation of scientific and
86. technological achievements in green technology. These in addition to promoting the
87. application of advanced technologies for energy conservation and environmental
88. protection as part of an optimal environment for technological innovation.
89. Furthermore, there is a need to enhance the level of human resources, technical
90. competencies and training provision to underpin the overall innovation capacity of
91. the Chinese transportation infrastructure. Finally, interregional technical cooperation
92. should be strengthened, particularly through expanding technical support from
93. regions with a higher technology development level to other regions with lower
94. levels.
95. *(2) Optimize the management approach to support CEE.* This study identified
96. that the deterioration of scale efficiency was the major reason curbing the CEE
97. growth. Therefore, there is a need for more robust preliminary research to inform
98. government strategies to ensure that the scale of transportation infrastructure
99. construction is compatible with local economic development plans. Adoption of an
100. integrated systems (like big data) for transportation infrastructure should enhance the
101. planning, coordination and linkage of national integrated transportation along with
102. the optimization of resources allocation. Also, this study has found that the level of
103. interaction in the East region with the outside world promotes the efficiency of basic
104. transportation carbon emissions. This allows achieving a win-win situation for
105. transportation infrastructure development and environmental protection. Therefore,
106. regarding the supervision of external capital, the Middle and West regions can learn
107. from the East region’s experience.
108. *(3) Implement differential ER.* This study identified that there are obvious
109. regional differences regarding the impacts of ER on CEE. After 2013, ER in the East
110. region had a significant negative impact. Therefore, the East region can reduce the
111. intensity of ER. For the Middle region, the impact was positive and stable in the long
112. term. Therefore, the Middle region can maintain the current level of ER intensity or
113. even moderately increase ER to observe whether CEE improves. For the West region,
114. the impact shifted between positive and negative, indicating the existence of an
115. inverse U-shaped relationship. Hence, the West region should keep its ER intensity
116. near its lowest value as much as possible.
117. *(4) Pay attention to the threshold effect of environmental regulations.* Research
118. shows that there is a threshold effect between ER and CEE. In the East region, when
119. environmental regulations are greater than the threshold, their role in promoting the
120. carbon emission efficiency of transportation infrastructure drops by about 96%.
121. Hence, continuing to increase the intensity of environmental regulations will likely
122. cause a sharp increase in governance costs, while carbon emissions efficiency will
123. not increase significantly. Therefore, the East region should carefully adjust the
124. intensity of environmental regulations in accordance with actual development needs
125. for the region. For the Middle region, when environmental regulations are greater
126. than the threshold, their promotion of CEE will drop to about 60%. At this point,
127. continuing to increase the intensity of environmental regulations can play a certain
128. role in promoting the growth of CEE. Therefore, when adjusting the intensity of ER
129. in the Middle region, a comprehensive assessment of the relationship between
130. governance costs and governance effects should be carried out to achieve a balance.
131. Unlike the East and Middle regions, the intensity of ER in the West region will have
132. a negative impact on CEE after reaching the threshold. Consequently, it can be
133. observed that the West region should keep environmental regulations below the
134. threshold whenever possible.

# 6. Conclusions

1. This research study evaluated the dynamic carbon emissions efficiency (CEE)
2. of China’s transportation infrastructure during the 2001-2017 period. The study
3. applied Hansen’s panel threshold model to analyze the threshold effects of
4. environmental regulations (ER) on CEE. The major findings are as follows:
5. (1) During the observation period, the CEE of China's transportation
6. infrastructure had a declining-rising-declining trend. During 2001-2006, CEE
7. decreased by approximately 4.9%, which was mainly caused by deterioration of
8. the production frontier. During 2007-2012, CEE increased slowly by
9. approximately 1.43%, which was mainly caused by technology progress and
10. improvement in the production frontier. During 2013-2017, CEE declined
11. sharply by approximately 7.24%. This was mainly caused by the deterioration of
12. scale efficiency and the production frontier.
13. (2) There are obvious regional heterogeneities in the CEE of transportation
14. infrastructure and its decomposition between the three Chinese regions analyzed.
15. The East region was obviously better than the Middle and West regions, while
16. the Middle region was slightly higher than the West region. As for its
17. decomposition, the pure technical efficiency of the East region was higher than
18. the other two regions, although its production frontier and scale efficiency was

lower than the West region in the same period.

1. (3) ER had a threshold effect on CEE. For the East and Middle regions,
2. there was a single threshold effect, with thresholds of 0.540 and 0.870
3. respectively. For the West region, there was a double threshold effect (thresholds
4. at 0.820 and 0.890). When ER in the East and Middle regions exceeded the
5. threshold, its positive impact on CEE was reduced. However, when ER in the
6. West region exceeded the threshold, its impact became negative.
7. This study has improved the evaluation methods and theoretical frameworks for
8. measuring the CEE of transportation infrastructure. This research has also provided
9. evidence-based recommendations for government decision-makers to formulate
10. improved ER policies. The major limitation of the study is that it did not consider
11. different types of regulation, which would have allowed a more fine-grained
12. discriminatory analysis. Hence, future research needs to be extended to explore how

different types of ER affect CEE.

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# Declaration of interests

1. The authors declare that they have no known competing financial interests or personal

relationships that could have appeared to influence the work reported in this paper.

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| 930 |  |

Highlight：

## Impact of Environmental Regulations on Carbon Emissions of Transportation Infrastructure: China’s Evidence

1. Using Chinese transportation infrastructure 2001-2017 panel data as an empirical study.
2. Carbon emission efficiency experienced a 10.15% decrease during 2001-2017.
3. The difference in carbon emission efficiency among regions is significant.
4. There is a non-linear relationship between ER and carbon emission efficiency.

**Declaration of interests**

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

* The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: