Trade in Renewable Energy Commodities among Regional Comprehensive Economic Partnership Countries: An Exploratory Study

By

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Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. A version of the material in Chapter 3 has been published, however, the research was conducted for the PhD degree. Apart from that, to the best of the author's knowledge, it contains no material previously published or written by another person, except where due reference is made in the text.

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Abstract

Renewable energy has become the optimal solution for mitigating the impacts of climate change and maintaining sustainable economic growth. Given the fact that Asia is a world leader in the manufacturing sector and the new driving force for global economic growth, the development of renewable energy is even more crucial for Asia-Pacific countries to ensure the security of energy supply and control the emissions of greenhouse gases. Although governments have offered a wide variety of administrative and financial support for the renewable energy industry, its expansion falls behind the schedule of National Determined Contributions (NDCs) which secures the achievement of the long-term goal of the Paris Agreement. Extra efforts are needed to boost renewable energy development, and trade in renewable energy commodities can play an important role in this process. Meanwhile, the establishment of the Regional Comprehensive Economic Partnership (RCEP) generates a solid platform for Asia-Pacific countries to enlarge such trade volume.

The first paper in this thesis aims to provide empirical evidence of the positive effects of the renewable energy commodities trade on renewable energy investments. It employs a two-step stochastic frontier analysis (SFA) to investigate and decompose the technical efficiency of investments in renewable energy electricity generation capacity. By using panel data consisting of 14 countries from 2004 to 2019, it finds that the average technical efficiency of the capacity investment was approximately 42 per cent in 2004 and increased to 58 per cent in 2019, which implies that invested capital is not used efficiently enough in installing new renewable energy power generation capacity. Furthermore, the impact of R&D investment in early stages on construction capacity is currently undervalued. Most importantly, the results show that imports of renewable energy goods, as well as innovations in the renewable energy sector, can significantly improve the technical efficiency of the capacity investment.

The second paper applies a gravity model with a metafrontier approach to evaluate

renewable energy commodities trade performance among RCEP members. It is assumed that different groups of countries may have different technologies and production frontiers for trade, and thus trade efficiency cannot be directly compared between groups. The metafrontier approach introduces a metafrontier that envelops all individual group frontiers to solve the difficulty in comparing technical efficiency scores across groups. This paper divides 11 countries into two groups based on their export volumes of renewable energy commodities from 2006 to 2015 to calculate each country's technical efficiency with respect to each group frontier (TEG) and its total technical efficiency with respect to the metafrontier (TEM). First, it finds that no country's average TEG exceeds 50 per cent, while TEGs in both groups gradually increase from 2006 to 2015. Second, the result supports the assumption that these two groups have different frontiers for trade, and the higher export volume group adopts relatively more effective technology as its group frontier is closer to the metafrontier than its counterpart. Combined, the TEM of the higher export volume group is 5 to 10 times that of the lower volume group. However, the highest TEM only scores 37.1 per cent, which illustrates that there are vast spaces for all RCEP countries to improve their trade efficiencies in renewable energy commodities within the region.

The third paper is designed to figure out which factors can influence the trade performance of renewable energy goods, especially the implicit trade cost. This paper uses a more complicated gravity equation with a one-step SFA method to analyse China's export frontier and export efficiency of renewable energy commodities to other RCEP members. Firstly, it reaffirms the finding in the second paper that significant implicit trade costs exist, namely the trade inefficiency term, in China's exports. Secondly, policy instruments related to the renewable energy sector in the exporting country have a significant positive impact on improving export efficiency. Thirdly, the size of the renewable energy market in the exporting country has a mixed effect on renewable energy commodities exports. On one hand, a larger renewable energy market would increase the export frontier. On the other hand, if growth in

renewable energy demand in the exporting country is relatively faster than the increase in supply, the expanding renewable energy market will reduce the export efficiency score. Finally, the estimation reveals that the innovation process in China becomes one of the implicit trade costs in its renewable energy commodities export, which suggests that current technical regulations and technology certification systems are inefficient to facilitate the technology transfer process between RCEP members.

Table of Contents

Declaration ..... **I**

Acknowledgements ..... **II**

Abstract ..... **IV**

Table of Contents ..... **VII**

List of Tables ..... **X**

List of Figures ..... **XI**

Chapter 1 Introduction **1**

1.1 Background of the thesis **1**

1.2 Context of empirical studies **3**

1.2.1 Technical efficiency of capacity investments 3

1.2.2 Potential for trade between RCEP members 3

1.2.3 Determinants for China's export frontier and trade inefficiency term 5

1.3 Organisation **5**

Chapter 2 The Impact of Trade on Technical Efficiency of Investment in Renewable Energy Electricity Generation Capacity **6**

2.1 Introduction **7**

2.2 Literature review **11**

2.3 Theoretical framework **14**

2.4 Model specification and data description **18**

2.4.1 Stochastic production function 18

2.4.2 Inefficiency decomposition 22

2.5 Results and discussion **24**

2.5.1 SFA regression results 24

2.5.2 Inefficiency decomposition results 27

2.6 Conclusion and policy suggestions 30

2.7 Appendix 2.I 36

2.8 Appendix 2.II 37

Chapter 3 The Trade Potential of Renewable Energy Commodities among RCEP Members 41

3.1 Introduction 42

3.2 Literature review 45

3.3 Theoretical framework 50

3.3.1 Illustration of the metafrontier approach 50

3.3.2 Group frontiers by SFA 53

3.3.3 Metafrontier by LP and QP 54

3.3.4 Metafrontier with SMF 56

3.4 Model specification and data description 58

3.5 Results and discussion 61

3.5.1 Group frontiers results 61

3.5.2 Metafrontier results 65

3.6 Conclusion 70

3.7 Appendix 3.I 73

3.8 Appendix 3.II 74

Chapter 4 Identifying Triggers and Barriers for Trade in Renewable Energy Commodities in RCEP Countries: Evidence Based on China's Export Data 81

4.1 Introduction 82

4.2 Literature review 86

4.3 Theoretical framework 88

4.4 Model specification and data description 91

4.5 Results and discussion 96

4.6 Conclusion 103

4.7 Appendix 4.I 107

Chapter 5 Conclusion 112

5.1 Summary of findings 112

5.2 Policy implications 113

5.3 Limitations and future research 115

References 116

List of Tables

Table 2.1 Data set statistical summary.....23
Table 2.2 Result of FE and RE regressions for lag selection and SFA regression.....25
Table 2.3 Results of technical inefficiency decomposition model by FE and RE.....29
Table 2.4 HS code of renewable energy commodities and descriptions.....37
Table 3.1 Data set statistical summary.....61
Table 3.2 SFA regression results for Group1, Group2, and the pooled data.....62
Table 3.3 Estimations of the technical efficiency scores with respect to the group frontiers.....65
Table 3.4 Estimations of the metafrontier function 66
Table 3.5 Estimations of the meta-technology ratios and the technical efficiency scores with respect to the metafrontier 67
Table 3.6 HS code of renewable energy commodities from the APEC 54 list 73
Table 3.7 TEG, MTR, and TEM estimates by LP, QP, and SMF.....74
Table 4.1 Data set statistical summary.....96
Table 4.2 Estimates of the determinants on China's renewable energy commodities exports to RCEP countries 97
Table 4.3 HS code of renewable energy commodities and descriptions.....107

List of Figures

Figure 2.1 Global new investment in renewable energy, 2004 to 2019, billion US dollars.....7
Figure 2.2 Newly added capacity of renewable energy electricity generation, 2004 to 2019, megawatt (MW).....9
Figure 2.3 Technical efficiency rates of capacity installation in 14 countries, 2006 and 2019.....28
Figure 2.4 Growth of the R&D investment ratio, world total, 2005 to 2019.....31
Figure 2.5 Growth of the R&D investment ratio, country, 2005 to 2019.....32
Figure 3.1 World total energy supply by source, 2000 to 2016, Exajoule (EJ).....42
Figure 3.2 Asia-Pacific and world total energy supply by source, 2016, in proportion 43
Figure 3.3. Metafrontier model illustration.....52
Figure 3.4 Estimations of MTR by SMF, LP, and QP 68
Figure 3.5 Estimations of TEM by SMF, LP, and QP.....68
Figure 4.1 Renewable energy electricity generation and installed capacity, 2005 and 2019, in proportion.....84
Figure 4.2 Exports of renewable energy commodities from China, 2006 to 2015, million US dollars.....85
Figure 4.3 Ratios of renewable energy supply in importing countries to China, 2006 to 2015.....100
Figure 4.4 Ratios of the number of cumulative patents in renewable energy technologies owned by importing countries to China, 2006 to 2015 102

Chapter 1 Introduction

1.1 Background of the thesis

Issues raised by climate change and the energy crisis have been in the limelight around the world. Sustainable Development Goal (SDG) 13, proposed in the 2030 Agenda for Sustainable Development, requires all members of the United Nations to 'take urgent action to combat climate change and its impacts'. Meanwhile, SDG 7 also calls to 'ensure access to affordable, reliable, sustainable, and modern energy for all'. As the largest source of greenhouse gas emissions is from the fossil energy used for electricity, heat, and transportation (Ritchie 2020), reform and development in the energy sector becomes one of the key determinants to maintain sustainable development for the world.

Under such a macro environment, facilitating the development of renewable energy technologies has become a consensus of all governments. At the 21st session of the Conference of the Parties (COP 21) of the United Nations Framework Convention on Climate Change (UNFCCC), participating countries adopted the Paris Agreement, which is the most significant and widely recognised international treaty regarding climate issues. The agreement aims to limit the rise in the global temperature to well below 2 °C, preferably to limit the increase to 1.5 °C, compared to pre-industrial levels. To reach this long-term goal, it requires all members to set their own targets and plans on the reduction of greenhouse gas emissions, known as Nationally Determined Contributions (NDCs). Renewable energy technology transfer and capacity installation are core targets of the NDCs.

Since 2017, the Climate Change Performance Index (CCPI) has evaluated the progress of 60 countries' NDCs. In its annual reports, the top three positions in the overall ranking have remained empty since 2017, as the CCPI considers that no country has performed well enough in achieving the Paris Agreement's goal.

Countries need to take more action to speed up the process of deploying renewable energy technologies.

Countries in the Asia-Pacific region are facing even tougher challenges regarding energy issues. Alongside significant economic achievements in the recent decade, the energy demand in Asia-Pacific countries is expected to maintain a fast growth rate. Meanwhile, according to the International Energy Agency (IEA), Asia-Pacific countries' energy supply still heavily relies on coal and oil sources. On the other hand, environmental issues have become increasingly serious in the area, having been previously treated as inevitable sacrifices and opportunity costs for economic growth. These countries have an urgent need to accelerate the deployment of renewable energy electricity generation capacity to solve the conflict between controlling greenhouse gas emissions and increasing energy supply to meet surging in energy demand.

This thesis provides evidence that trade in renewable energy commodities can play an important role in developing the renewable energy power generation sector. Many studies have investigated the relation between trade in renewable energy goods and greenhouse gas emissions (Sebri & Ben-Salha 2014; Jebli & Youssef 2015; Tiba *et al.* 2016, *etc.*). This thesis shows the effect of trade from a new angle, that is, that it can improve the efficiency of capital investment in the construction of renewable energy electricity generation capacity. With this conclusion, the establishment of the Regional Comprehensive Economic Partnership (RCEP) is a great chance for Asia-Pacific countries to expand their renewable energy sectors via enhancing trade in renewable energy commodities within the region. This thesis measures how effective the RCEP agreement could be in terms of improving trade between RCEP members. Furthermore, it also figures out which factors can improve such trade values.

1.2 Context of empirical studies

1.2.1 Technical efficiency of capacity investments

The most straightforward way to boost the renewable energy sector is to attract more investment. According to Bloomberg New Energy Finance (BNEF), the yearly total investment in renewable energy capacity installation increased from 45 billion dollars in 2004 to 338 billion dollars in 2017, then decreased to 317 billion dollars in 2019. As the total capacity investment in renewable energy reached a relatively significant level, how well these investments are used in the construction phase becomes more and more important. If the efficiency of capital input's usage can be improved, the newly installed renewable energy power generation capacity will continue to increase, even if the amount of investment and construction costs remain unchanged. However, to the best of the author's knowledge, no research has been done to study the efficiency problem in this area.

The first paper employs a two-step SFA method to investigate whether capacity investments are efficiently used in constructing renewable energy power plants. By using panel data consisting of 14 countries from 2004 to 2019, the regression results indicate the presence of a technical inefficiency term in the construction phase of renewable energy power generation capacity. Moreover, the technical inefficiency is decreasing over time. This finding suggests that the improvement of capacity investments' performance has become a driving force in the increase in installed capacity. In addition, the estimation proves that trade in renewable energy commodities has a positive and significant effect in reducing the technical inefficiency. It attributes this improvement to the technology transfer embodied in imports and the corresponding service trade.

1.2.2 Potential for trade between RCEP members

As the first paper confirms the effect of renewable energy commodities trade on the

development of renewable energy power generation sector, the establishment of RCEP provides a great platform for members to deepen collaboration in renewable energy technologies. However, how effective the RCEP agreement could be remains unanswered in the literature. To answer this question, trade resistances need to be identified. Conventionally, trade resistances contain transport costs, tariffs, exchange rates, and some other proxies such as whether the country is landlocked. However, McCallum (1995) finds consequential resistances that reduce trade beyond the border compared to trade within the border. This kind of trade cost is described as the implicit trade cost in the thesis. More specifically, the implicit trade cost refers to trade resistances that cannot be easily quantified, such as institutional barriers and infrastructure constraints. The implicit trade cost affects trade flows via reducing trade efficiency scores. Anderson and van Wincoop (2004) also conclude that international trade costs are very large and underestimated in the conventional gravity model, and the measurement of trade costs needs to be improved.

The second paper adopts the gravity model with a metafrontier approach to measure trade inefficiency. One advantage of the metafrontier approach is that it allows objectives to have different technology sets. To achieve this goal, the total technical inefficiency is decomposed into two components, which are the usual trade inefficiency term and the technology gap. This paper divides 11 RCEP countries into two groups based on trade values and assumes that each group has its unique technology set. The estimation result indicates that bilateral trade in renewable energy commodities between RCEP members is located in a relatively low position. The implementation of the RCEP agreement could vastly improve trade values by reducing the implicit trade cost and realising more trade potentials. Second, countries with higher export values enjoy a more advanced technology set than their counterparts.

1.2.3 Determinants for China's export frontier and trade inefficiency term

Which factors contribute to the implicit trade cost, namely the trade inefficiency term, becomes an interesting question, as the second paper illustrates that the implicit trade cost is the main barrier for the renewable energy commodities trade. The third paper applies an augmented gravity equation with a one-step SFA method to analyse China's exports to other RCEP members.

This paper reveals that the renewable energy policies issued in China can effectively improve its export efficiency, while the non-tariff measurements imposed by importing countries have a significant and opposite effect. Second, the expansion of China's renewable energy market has a mixed effect on the export value. Certainly, a larger market size represents a stronger supply force, which determines a larger export frontier. However, the results show that a larger market size also reduces trade efficiency scores. Most importantly, the innovation process in China is found to be negatively correlated with the trade efficiency score. This finding strongly recommends that more efficient technical regulations and standards should be established under the RCEP scheme.

1.3 Organisation

This thesis contains five chapters: this introduction, three main empirical studies, and a conclusion. Chapter 2 investigates technical inefficiency in investment in renewable energy electricity generation capacity installations, and it shows the effect of trade in renewable energy commodities on the technical inefficiency term. Chapter 3 estimates the impacts of the implicit trade cost and the technology gap on the efficiency scores of renewable energy commodities exports within the RCEP region. Chapter 4 analyses which factors can influence the export frontier and the technical inefficiency of China's renewable energy goods export to other RCEP members. Chapter 5 summarises the key findings and makes policy suggestions.

Chapter 2 The Impact of Trade on Technical Efficiency of Investment in Renewable Energy Electricity Generation Capacity

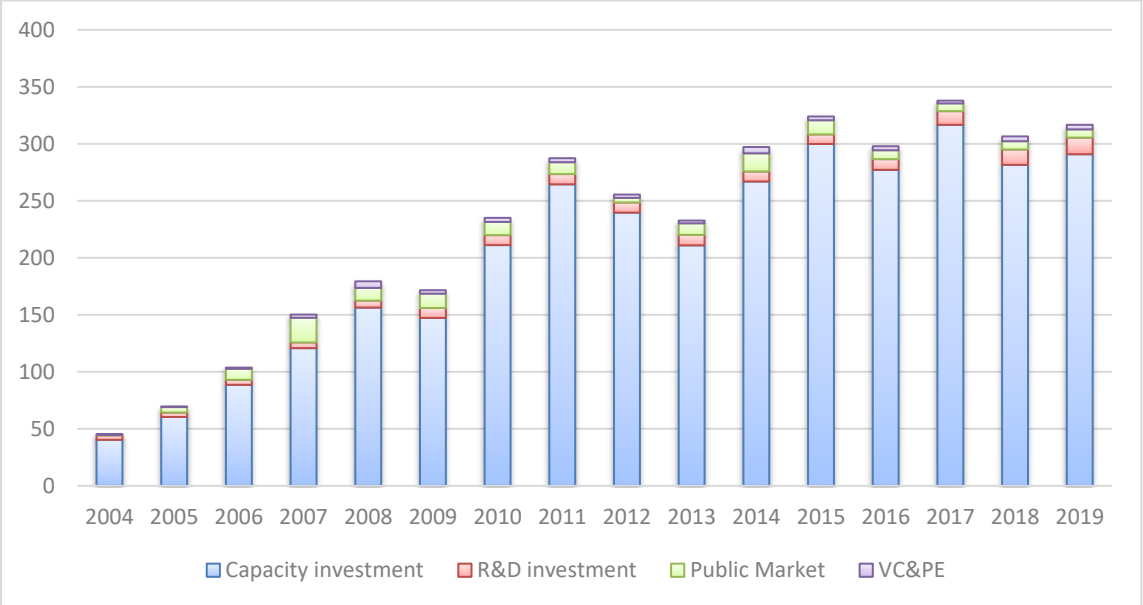
Summary

As investment in renewable energy power generation capacity exceeds 300 billion dollars per year, the performance of these capacity investments becomes more and more noticeable. This paper uses a two-step stochastic frontier analysis (SFA) method to firstly evaluate the technical efficiency of electricity generation capacity investment, then it examines the impact of imports on the technical inefficiency term, based on a panel data set of 14 countries between 2004 and 2019. Firstly, the findings demonstrate that the technical efficiency of capacity investment varies from 23 percent to 88 percent, and it is increasing over time. Secondly, the innovation process in renewable energy technologies, the import of renewable energy-related commodities, and cost reductions in building renewable energy plants have significantly positive impacts on inefficiency reduction.

2.1 Introduction

By signing the Paris Agreement and claiming Nationally Determined Contributions (NDCs), all parties show their ambitions to achieve sustainable development, alleviate climate change, and eventually eliminate greenhouse gas emissions. Investment in renewable energy projects plays a crucial role in accomplishing these long-term goals. With the development of renewable energy technology, the future of renewable energy electricity generation is all about access to finance (Taghizadeh-Hesary & Yoshino 2020). A large amount of research has been conducted on how to promote investment in renewable energy, especially by government instruments (*e.g.*, Alolo *et al*. 2020; Owen *et al*. 2018; Chen *et al.* 2021). Meanwhile, total renewable energy investment experienced a considerable increase over the past two decades. Figure 2.1 shows the value of new renewable energy investment in the world from 2004 to 2019.

Figure 2.1 Global new investment in renewable energy, 2004 to 2019, billion US dollars



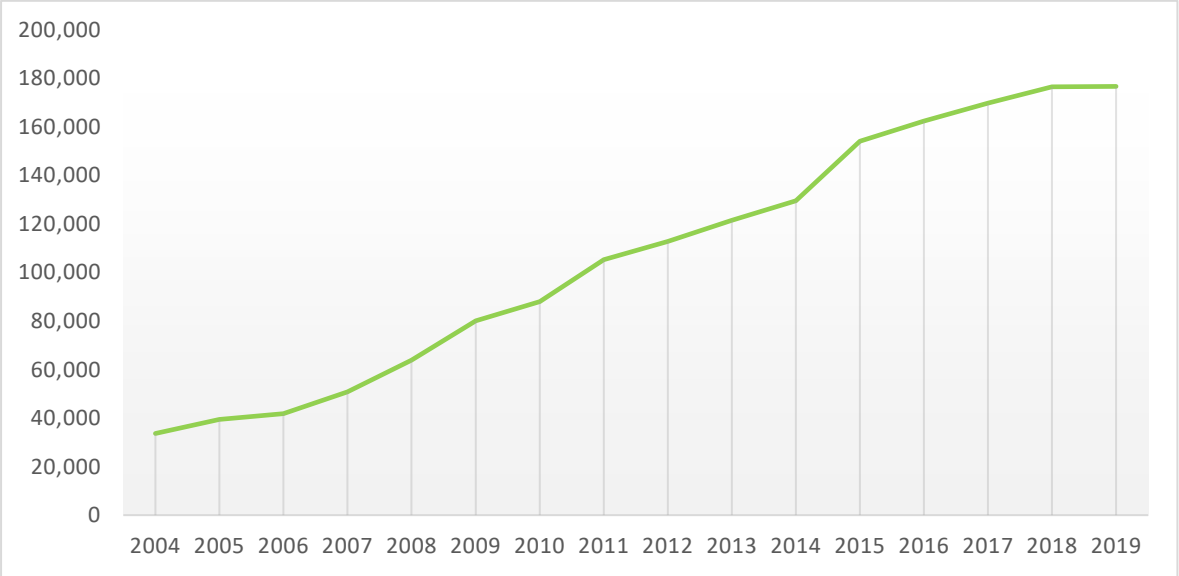
Note: Renewable energy excludes large hydropower in this paper.

Source: Bloomberg New Energy Finance (BNEF).

According to *Global Trends in Renewable Energy Investment* report (GTR) 2020, total investment in renewable energy can be decomposed into capacity investment, research and development (R&D) investment, public market, and venture capital and private equity (VC&PE). Capacity investment is defined as all money invested in renewable energy generation projects, large or small. It covers both asset finance of utility-scale projects, whether from internal company balance sheets, from loans, or from equity capital, and the financing of small-scale solar systems of less than 1MW. R&D investment covers all money invested in early-stage renewable energy technologies and techniques, whether financed out of government budgets or from the balance sheets of specialist renewables companies. Finally, VC&PE refers to all money invested by venture capital and private equity funds in the equity of specialist companies developing renewable energy technology. Similarly, public market refers to all money invested in the equity of specialist publicly quoted companies developing renewable energy technology and clean power generation.

It can be seen from Figure 2.1 that global total renewable investment peaked in 2017 at 325.6 billion dollars, which is almost eight times the value in 2004. In addition, increments are mainly from increases in capacity investment, and capacity investment takes the dominant position in total investment. Similarly, newly added renewable energy electricity generation capacity also increased dramatically during this period (see Figure 2.2).

Figure 2.2 Newly added capacity of renewable energy electricity generation, 2004 to 2019, megawatt (MW)



Source: International Renewable Energy Agency (IRENA) statistics.

Figure 2.2 shows that newly installed renewable energy power generation capacity increased from 33,672 MW in 2004 to 176,800 MW in 2019, although the figures in 2018 and 2019 are almost the same. By comparing capacity investment data with newly added capacity data, opposite trends can be found, that is, the investment curve fluctuated more while newly added capacity kept increasing, for example, in the period from 2011 to 2014. Of course, this could be attributed to the rapid cost reduction in renewable energy technology. However, the technical efficiency of installing renewable energy power generation capacity must be considered to illustrate this deviation.

There are several different meanings of the term efficiency in the energy sector, and at least two of them are relevant to electricity generation. Generally, two phases should be involved in developing electricity supply from nothing: the construction phase, which uses capital and labour inputs to establish the electricity generation capacity, and the production phase, which combines energy inputs and other operational costs

with the installed capacity to produce electricity. The efficiency of the production phase is the electricity generation efficiency, which can be treated as a kind of energy conversion efficiency, and it has been widely evaluated in the literature. This paper aims to estimate efficiency in the construction phase.

The technical efficiency estimated in this paper refers to how productive capacity investment can be in producing renewable energy electricity generation capacity, if all other things are unchanged. Higher technical efficiency means that the same amount of capacity investment can deliver more installed capacity than before with all costs, inputs, and technology unchanged. Therefore, a significant improvement in technical efficiency could possibly explain why newly added capacity continues increasing when investment decreases. However, to the best of the authors' knowledge, the impact of technical efficiency has not been assessed in the current literature. So, one contribution of our paper is to address the technical efficiency problem in the renewable energy power generation sector in the construction phase.

In addition, only a few researchers have recognised the importance of the role that international trade (cooperation) plays in developing the renewable energy power generation sector. While some papers show that trade liberalisation has an impact on energy policies, the direct linkage between trade and renewable energy investment or electricity generation capacity is seldom demonstrated (Bellakhal *et al.* 2019). By introducing a technical inefficiency term, our research demonstrates the effect of trade on the development of the renewable energy sector from a new angle, which is our second main contribution to the existing literature.

By applying stochastic frontier analysis (SFA), this research calculates the technical efficiency rates in 14 countries from 2004 to 2019. Firstly, it finds that the technical efficiency of capacity investment varies among different countries and significantly increased over the sample period. Secondly, trade (imports) in renewable energy-related commodities can effectively improve technical efficiency in installing

renewable energy power generation capacity. Additionally, this paper also shows that cost reduction in renewable energy electricity generation does not directly increase the capacity, but it still works via promoting the technical efficiency of capacity investment.

The rest of this paper is structured as follows. Section 2 reviews the existing literature. Section 3 elaborates the SFA model in detail. Section 4 constructs and discusses the model and data set. Section 5 shows the results of the empirical work, and Section 6 gives conclusions.

2.2 Literature review

This study is related to the research topic in capacity investment, or total renewable energy investment, while a large literature focuses on how to induce more investment in renewable energy technology. First of all, many researchers study the impacts of mandatory government instruments, such as feed-in tariffs and capacity subsidies, on renewable energy investment. For example, Bolkesjo *et al*. (2014) show that feed-in tariffs significantly positively affect wind energy investments; Alolo *et al*. (2020) further illustrate that feed-in tariffs and feed-in premiums are positively related to both wind and solar photovoltaic energy investment. Secondly, some papers demonstrate the importance of access to finance in renewable energy investment. Owen *et al*. (2018) and Taghizadeh-Hesary and Yoshino (2020) state that governments should increase the role of public financial institutions and non-banking financial institutions to fill the financing gap in renewable energy. Taghizadeh-Hesary and Yoshino (2019) suggest that green credit guarantee schemes should be established to boost and reduce the risk for private investment in green energy projects. Moreover, some research examines the effectiveness of market incentive mechanisms, such as carbon taxes, on attracting renewable energy investment. Chen *et al.* (2021) indicate that investment in renewable energy increases with a higher carbon price, and cap-and-trade mechanisms are relatively more attractive for utility firms to invest in

renewable energy, compared with mandatory government instruments. Another stream of papers analyses factors or risks for renewable energy investments from a perspective of multiple criteria decision-making (Mi & Liao 2020). For instance, Wu *et al.* (2020) comprehensively assess six major types of risks for China's renewable energy investment in Belt & Road initiative countries by an ANP-cloud model. All of these papers contain an intuitive assumption that renewable energy investment drives the development of the renewable energy electricity sector, while none of them numerically shows the marginal effect of investment on renewable energy electricity generation or installed capacity.

Data envelopment analysis (DEA) has been widely applied in calculating efficiency scores for the electricity generation sector by a large number of researchers, however, most previous studies focus on electricity generation efficiency instead of technical efficiency as mentioned above. One primary stream of research employs installed capacity or capital (both financial and material resources) and labour inputs used in production as main explanatory variables, and electricity generation or other simulation indicators, such as total business income, as explained variables to measure electricity generation efficiency at industrial, regional, and national levels, respectively (*e.g.*, Saglam 2017; Ervural *et al*. 2018; Wu *et al*. 2016; You & Jie 2016). Zeng *et al*. (2018) measure the investment efficiency of the new energy industry in China by applying a four-stage DEA. However, they use total gross income as the dependent variable, which means that the estimated efficiency is more like a combination of technical efficiency and electricity generation efficiency. Similarly, Kim *et al*. (2015) and Lin and Luan (2020) estimate innovation efficiency by linking R&D investment to total power generation volume and operating profit, respectively. Particularly, Ederer (2015) measures the cost efficiency of offshore wind energy capacity by treating capital cost and operational cost as the input factors. More comprehensive reviews can be found in the work of Sueyoshi *et al*. (2017) and Mardani *et al*. (2017). To the author's best knowledge, none of those studies examines

the technical efficiency of investment in the stage of installing electricity generation capacity.

There exists another stream of papers that studies the efficiency-related problem of renewable energy investment, where term efficiency refers to costs and policy effectiveness of government instruments. For example, Ozdemir *et al*. (2020) argue that capacity-oriented and energy-oriented policies have different market impacts on renewable energy development, and if the target is to reduce renewable energy costs through learning-by-doing (increasing capacity), energy-oriented policies, such as feed-in tariffs and feed-in premiums, would induce inefficient investment. Neuhoff *et al*. (2017) also address the cost-effectiveness problem in renewable energy electricity production, but they consider cost-efficiency as system-friendly installations. These explanations of efficiency are different from what this paper wants to measure by SFA. The literature on SFA will be reviewed in the methodology section.

Related to the second research question in this paper, a strand of research tests the causality relationship between trade and renewable energy consumption when analysing the Environmental Kuznets Curve. Jebli *et al*. (2015) consider and show the presence of long-run bidirectional Granger causality between trade (exports or imports) and renewable energy consumption by employing a panel of 24 sub-Saharan African countries over the period 1980 to 2010. Chen *et al*. (2019) find a different but similar result that foreign trade is the Granger reason for renewable energy consumption in the long run, and there is bidirectional causality between trade and renewable energy consumption in the short run with China's data. However, this research lacks the presence of renewable energy investment, and our paper focuses on renewable energy power generation capacity instead of renewable energy consumption.

Bellakhal *et al.* (2019) might be the most relevant research paper which examines the relationship between renewable energy investment, governance, and trade by using

data from 15 Middle Eastern and North African countries from 1996 to 2013. They find that trade (trade openness index) has a significantly positive effect on renewable energy investment which is expressed as the share of renewable energy in total primary energy produced. Moreover, by introducing an interaction term between governance and trade openness in their regression, they also argue that part of this effect of trade is indirect, in that it works through reducing the negative effects of weak governance or impacting environmental policy. In contrast to Bellakhal *et al.* (2019), this paper investigates the relationship between trade and the technical efficiency of renewable energy investment in capacity installation, not the capacity investment itself.

2.3 Theoretical framework

This paper employs stochastic frontier analysis (SFA) to estimate the technical efficiency, or 'production efficiency', of investment in renewable energy power generation capacity. Firstly and independently proposed by Aigner *et al*. (1977) and Meeusen and van den Broeck (1977), the stochastic frontier production function has been widely adopted to investigate the technical efficiency problem, which can be treated as a component of total factor productivity, in various economic research fields. For instance, in the agriculture industry, Kompas *et al*. (2004) use SFA to analyse technical efficiency problems in fisheries; Kompas *et al.* (2010) apply this method to evaluate productivity and efficiency rice production in Vietnam. Another strain of research that intensively employs SFA is international trade. For example, Kalirajan (2007) introduces the stochastic production frontier into the conventional gravity model to estimate the bilateral trade efficiency of Australia. In short, SFA is undoubtedly a proper method for studying one type of question that asks what the maximum output could be given an existing input combination, which exactly covers the first and most important research question in this paper. More detailed introductions can be found in the work of Kumbhakar and Lovell (2000) and Coelli *et*

al. (2003).

The main idea of SFA is that it separates a random component, which must be non-negative in the production function, from the error term to measure the value of technical efficiency given inputs and the existing technology. According to Battese and Coelli (1995), this concept is also valid for panel data by introducing a time trend to the technical inefficiency term. To illustrate in detail how to construct a stochastic frontier production function and how it works, I would like to start from a conventional production function:

$$Y_{it} = f(X_{it}, \beta) \tag{1}$$

Equation (1) shows that in time *t*, given *X* input, the *i*th panel member would produce *Y*. As mentioned above, SFA assumes that each panel member could only produce at most no more than its full production capacity. Also, it assumes that not all panel members will be full production capacity because of the existence of technical inefficiency. Furthermore, random shocks would also have impacts on output in reality. Therefore, another two variables are generated to capture these effects.

$$Y_{it} = f(X_{it}, \beta)\xi_{it}\exp(v_{it}) \tag{2}$$

In equation (2), ξ_{it} is the level of technical efficiency for member *i* at time *t*, while v_{it} represents the effect of random shocks. There are two restrictions for the value of ξ_{it}. Firstly, because the output is assumed to be strictly positive, ξ_{it} must be positive. Secondly, ξ_{it} cannot take a value larger than 1, as $\xi_{it} = 1$ means that the production process achieves its maximum output level under current technology. Therefore, ξ_{it} takes a value between 0 and 1 ($0 < \xi_{it} \leq 1$).

To transform equation (2) into a linear expression, a natural logarithm transformation is performed, which gives equation (3):

$$\ln Y_{it} = \ln f(X_{it}, \beta) + \ln \xi_{it} + v_{it} \tag{3}$$

It is assumed that the production function is linear in logarithm, such as a Cobb-Douglas production function, in which there are *k* kinds of inputs. Finally, by generating a new variable u_{it} which is defined as $u_{it} = -\ln \xi_{it}$, equation (3) will convert into:

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{k} \beta_j \ln X_{jit} - u_{it} + v_{it} \quad (4)$$

Equation (4) is the form of the stochastic frontier production function that our model uses. In the above equation, β_j is a vector of parameters of inputs (or control variables) to be estimated. The error term u_{it} measures the technical inefficiency, and $u_{it} \geq 0$ because of the restriction $0 < \xi_{it} \leq 1$. This non-negative term ensures that our estimation of the stochastic production frontier, $E(Y_{it}|u_{it} = 0, X_{it})$, always lies beyond the actual output Y_{it}. Based on this equation, the technical efficiency of the *i*th panel member at time t, TE_{it}, could be expressed as:

$$TE_{it} = \frac{Y_{it}}{E(Y_{it}|u_{it}=0, X_{it})} = \exp(-u_{it}) \quad (5)$$

which is the ratio of observed output to predicted production frontier, namely the optimal or potential production. Equation (5) suggests that the estimation of each panel member's u_{it} denotes its technical efficiency calculation.

SFA uses the maximum-likelihood (ML) method to estimate the parameters in the stochastic production function. However, neither u_{it} nor v_{it} of each individual can be directly observed. By estimating equation (4) using sample data and a ML estimator, only a combined error term, $(-u_{it} + v_{it})$, could be obtained, which is the difference between actual production and the predicted production frontier. Therefore, restrictions must be imposed on their distributions to separate u_{it} and v_{it} from the combined error term. Normally, it is assumed that u_{it} follows a truncated normal distribution $u_{it} \sim N^{+}(u, \sigma_u^2)$, and v_{it} is normally distributed $v_{it} \sim N(0, \sigma_v^2)$. In practice, the maximum likelihood regression gives the estimation of u_i, while u_{it} is

calculated by introducing a time trend to u_i. According to Coelli *et al.* (2003, p. 188), the likelihood function is expressed in terms of the variance parameters:

$$\ln(L) = -\frac{N}{2}\ln\left(\frac{\pi}{2}\right) - \frac{N}{2}\log(\sigma^2) + \sum_{i=1}^{n}\ln[1-\phi(z_i)] - \frac{1}{2\sigma^2}\sum_{i=1}^{n}(\ln y_i - x_i\beta)^2 \quad (6)$$

$$where\ \sigma^2 = \sigma_u^2 + \sigma_v^2, \gamma = \frac{\sigma_u^2}{\sigma^2}, and\ z_i = \frac{\ln y_i - x_i\beta}{\sigma}\sqrt{\frac{\gamma}{1-\gamma}}$$

The estimations of parameters in equation (4) can be obtained by solving the maximum value of equation (6).

One post-estimation application of SFA is to construct a technical inefficiency decomposition model with the predicted value of u_{it}. It answers what factors have an influence on technical inefficiencies or efficiencies, a question that is even more attractive to researchers sometimes. Typically, a technical inefficiency decomposition model uses a linear specification form for tractability, and usually includes an intercept (Grafton *et al*. 2006). If there exist *m* determinants of technical inefficiencies by assumption, the decomposition model will follow the form

$$u_{it} = \delta_0 + \sum_{l=1}^{m}\delta_l Z_{lit} + w_{it} \quad (7)$$

where u_{it} is estimated via the stochastic frontier model, Z_{lit} is a vector of independent variables (determinants), δ_l is a vector of parameters to be estimated, and w_{it} is an additional random error term. The combined regression process, equation (4) and equation (7), is called two-step SFA.

In summary, this paper applies the SFA model with two stages[1]. Firstly, it establishes a stochastic frontier production function in the form of equation (4) to predict the technical efficiency of investments used in building renewable energy power generation capacity. Secondly, with the estimation of u_{it} from the first step, it uses the technical inefficiency decomposition model in the form of equation (7) to identify which components would affect the inefficiency term and to quantify their marginal effects. Maximum likelihood estimation (MLE) and fixed-effect (FE) and random-effect (RE) will be used to estimate equation (4) and equation (7), respectively[2].

2.4 Model specification and data description

2.4.1 Stochastic production function

To measure technical efficiency, this paper uses the newly installed power generation capacity in each year as the dependent variable to represent the output of capacity investment. Electricity generation is an alternative option to work as the dependent variable. The advantage of using electricity generation is that it is a more intuitive concept as currently the goal of developing renewable energy technology is to increase the proportion of renewable energy sourced electricity in total power generation. However, as discussed above, the usage of electricity generation or its simulation indicators would involve the value of electricity generation efficiency,

[1] In the literature, many papers (*e.g.*, Battese and Coelli 1995) argue that equations (4) and (7) should be estimated simultaneously, which is commonly called one-step SFA. However, the following reasons are given for using the two-step procedure: The production, newly installed generation capacity, is directly influenced by the core variables in equation (4), such as new capacity investment and labour, while the explanatory variables in equation (7), such as patent, influence the technical efficiency and not the production variable directly (Kalirajan 1981; Bhende & Kalirajan 2007). Since technical efficiency influences the output indirectly, its impact needs to be analysed indirectly without entering it in the production function directly (Johnson,1967).

[2] Nevertheless, the method of simultaneously estimating the production function and the technical inefficiency function has also been demonstrated later in Chapter 4.

which can cause an overestimation problem.

Capacity investment, of course, is the most important explanatory variable, or input variable, in our model. According to GTR (2020), capacity investment refers to all money invested in renewable energy power generation projects, large or small. It covers both asset finance of utility-scale projects, whether from internal company balance sheets, from loans, or equity capital, and the financing of small-scale solar systems of less than 1MW. However, the value of the capacity investment variable actually used in this paper also includes the value of other types of investments in renewable energy, which are VC&PE and public markets and acquisition activity. The GTR reports consider that the development of renewable energy technology consists of four stages, technology research stage, the technology development stage, manufacturing scale-up stage, and rollout stage. Different kinds of investments would step into the process at different points, while the last two stages are the time when investments are mainly involved in capacity establishment. GTR (2020) states that VC&PE usually starts to engage in the technology research stage and lasts until the manufacturing scale-up stage, and public markets and acquisition activity occurs in the last two stages. Therefore, we consider the combined value a rational measurement for the total capacity investment.

Research and development (R&D) investment works entirely differently from all the other types of investments in renewable energy mentioned above. Following GTR (2020), R&D investment in this paper refers to money invested in early-stage renewable energy technologies and techniques, whether financed out of government budgets or from the balance sheets of specialist renewables companies. It can be intuitively recognised from the definition that R&D investment does not directly contribute to the establishment of generation capacity, but it plays a fundamental role at the construction decision-making stage. Thus, we introduce a control variable, the ratio of R&D investment to total investment in renewable energy, to capture the effect

of R&D investment on capacity construction.

Labour force is another primary explanatory variable. Because we cannot directly observe the labour input used in the capacity production process, we use the total advanced labour force supply as a substitute. The advanced labour force is defined as the economically active population aged between 15 and 64 with advanced education qualification. One thing that needs to be noted is that the quality of the advanced labour force varies across countries. Theoretically, the quality of labour inputs could affect total output through its impact on production efficiency. This means that the variation of labour quality does not affect the estimation result of the first stage regression, as the impact of production efficiency has been captured by the technical inefficiency term. However, the variation may have an impact on the technical inefficiency decomposition.

This study also takes the prices of capital inputs into consideration. The economic principle illustrates that, given all inputs measured in total value, the lower the input price is, the more the output would be, despite all inputs remaining the same. Although we could not directly obtain the price variable of inputs, such as the price of the generation module, Levelized Cost of Electricity (LCOE) is an available substitute that could be used as an estimator of input prices. LCOE is a measure of the average net present cost of electricity generation for a generating plant over its lifetime, which means that the calculation of LCOE includes expenditures in capital per unit of electricity generation. According to its formula (see Appendix 2.I), a decrease in capital price would cause a reduction in LCOE. Because of data limitations, our model uses a weighted average of LCOE of onshore wind energy and solar PV as a control variable.

Another exceedingly important factor that needs to be considered is lagged term, because of the construction period. The construction period of a renewable energy farm is relatively and significantly short compared with conventional fossil and

nuclear power plants. According to WindEurope (EWEA), a 10 MW wind farm can easily be built in two months, and a larger 50 MW wind farm can be built in six months. Solar farms require even less time. For example, it only took eight months to build the Kamuthi solar facility in Tamil Nadu, India, which has a total generation capacity of 648 MW. However, this only accounts for construction time. Planning and regulatory approval may also take a quite considerable proportion of the time. Besides, the 'one year' construction period is measured by calendar year while, when it comes to financial years, the construction may be finished over two or even three years. Therefore, it is reasonable to include lagged independent variables to assess the effects of the investment on future periods. Eventually, the stochastic frontier production function in this paper is specified as

$$\ln Cap_{it} = \beta_0 + \beta_1 \sum_{p=0}^{n} \ln Capin_{it-p} + \beta_2 \ln Lab_{it} + \beta_3 \sum_{q=0}^{m} R\&Dinr_{it-q}$$

$$+\beta_4 \ln wLCOE_{it} - u_{it} + v_{it} \quad (8)$$

This paper employs a balanced panel data set to estimate equation (8), where *t* is the time period from 2004 to 2019, and *i* represents a cross-section of 14 countries: Brazil, Canada, China, Denmark, France, Germany, India, Italy, Japan, Mexico, Spain, Sweden, the UK, and the USA.

Cap is the newly added installed generation capacity, excluding large hydropower plants, data for which is collected from IRENA statistics. *Capin* represents the new capacity investment each year, and data is provided by Bloomberg New Energy Finance (BNEF). *Lab* is the advanced labour force supply in each country. Data for *Lab* is collected from ILOSTAT for all panel members except China, whose figures are gathered from the China Statistical Yearbook (2005-2020). *wLCOE* is the weighted average of LCOE of onshore wind energy and solar PV, and data is provided by IRENA and BNEF. *R&Dinr* is the proportion of R&D investment in total investment in renewable energy, both of which can be found in BNEF. One thing that

needs to be noted is that both *R&Dinr* and ln*wLCOE* are not stationary time series (other dependent and independent variables are stationary); *R&Dinr* is integrated into order one while ln*wLCOE* is a trend-stationary process. Therefore, to avoid spurious regression results, this study uses the first difference of *R&Dinr* and detrend-ln*wLCOE* in estimation, which are shown as *d.R&Dinr* and deln*wLCOE* in the results, respectively. μ_{it} is the technical inefficiency term to be estimated. MLE is used to estimate the parameters, and it is expected that ln*Capin*, ln*Lab* and *d.R&Dinr* will have positive parameters while deln*wLCOE* is negative.

2.4.2 Inefficiency decomposition

For the second stage, this paper adopts three explanatory variables in the technical inefficiency decomposition model, which are patents in renewable energy sectors, the imports of renewable energy sector goods from the world, and *wLCOE* in each country. This defines the model as:

$$u_{it} = \delta_0 + \delta_1 Patent_{it} + \delta_2 Im08_{it} + \delta_3 wLCOE_{it} + w_{it} \quad (9)$$

Similar to stochastic frontier estimation, a balanced panel data set is used to estimate equation (9). u_{it} is the estimated technical inefficiency from stage one. Variable *Patent*, gathered from IRENA, is the cumulative patents in the renewable energy sector, which is based on the data from EPO PATSTAT and uses the Climate Change Mitigation Technologies (Y02) classification by EPO. *IM08* represents the imports of renewable energy-related commodities, collected from UN Comtrade. Appendix 2.II provides a detailed list of renewable energy-related commodities, which is selected from APEC 54 List and Wind (2008), based on 6-digital HS code classification. *wLCOE* remains the same as in the first regression.

Both FE and RE regression are operated to generate the parameters. Apparently, increments in patent numbers are the main driving force that improves production technology efficiency, so *Patent* is predicted to be negatively correlated with the

technical inefficiency term. Battese and Coelli (1995) state that input variables in the stochastic frontier production function may also be included in the technical inefficiency decomposition model. Grafton *et al*. (2006) further illustrate that a variable could belong in both models if it is considered to have effects on both the production frontier and technical inefficiency. As shown in Appendix 2.I, the calculation of LCOE involves other factors, such as operational and maintenance costs, rather than expenditure in the construction phase, which may be positively associated with technical inefficiency. So, it is rational to include *wLCOE* in both stages and expect a positive coefficient for it. We will discuss the mechanisms of *IM08* in the next section while we predict that it has a negative sign.

This study also considered including other variables in the inefficiency decomposition. For example, as discussed above, the quality of the advanced labour force may have an impact on the production inefficiency, and macroeconomic environment, such as the financial system, may also affect the efficiency of capital investment. However, due to the data limitations, these variables cannot be directly added to the model, which leaves room for future studies.

The following table (Table 2.1) shows the statistical summary of the data set.

Table 2.1 Data set statistical summary

Variable	Unit	Mean	Std. Dev.	Min	Max
Cap	MW	6175.12	12155.6	2	79841.02
Capin	$million	12093.02	19672.46	1.5	141700
R&Dinr	ratio	0.0824	0.1346	0.0004	0.9852
Lab	thousand	20213.16	24003.87	812.1	118230.8
wLcoe	$/MWh	122.19	76.27	43	542.96
Patent	thousand	20.62	39.75	0.007	241.09
IM08	$billion	11.03	13.86	0.6536	68.65

Source: Author’s calculation.

2.5 Results and discussion

2.5.1 SFA regression results

Before running stochastic frontier regression, it is necessary to identify the optimal lags used in the SFA model, namely *m* and *n*. Optimal lags are determined by applying FE and RE to regress equation (8) without the technical inefficiency term u_{it}. Results of FE and RE regression are shown in Table 2.2.

Table 2.2 Result of FE and RE regressions for lag selection and SFA regression

Dependent variable: ln *Cap*

Variables	FE		RE		SFA
	(1)	(2)	(3)	(4)	(5)
ln $Capin_t$	0.4478***	0.4856***	0.4546***	0.5209***	0.4989***
	(0.1112)	(0.1119)	(0.1137)	(0.1150)	(0.1018)
ln $Capin_{t-1}$	0.2929**	0.3257***	0.2887**	0.3202***	0.2972***
	(0.1332)	(0.1106)	(0.1391)	(0.1134)	(0.0981)
ln $Capin_{t-2}$	0.1262		0.1694		
	(0.1036)		(0.1049)		
ln Lab_t	0.9236***	-0.3188	0.1824**	0.1985**	0.2532***
	(0.3233)	(0.5064)	(0.0779)	(0.0820)	(0.0841)
d.$R\&Dinr_t$	1.8145**	2.1113***	1.8020**	2.3188***	2.3449***
	(0.8074)	(0.7520)	(0.8414)	(0.7775)	(0.6982)
d.$R\&Dinr_{t-1}$	0.9273	1.5221***	0.8712	1.6331***	1.4777***
	(0.7923)	(0.4768)	(0.8228)	(0.4913)	(0.4551)
d.$R\&Dinr_{t-2}$	-0.4149		-0.2033		
	(0.4898)		(0.5034)		
ln $wLcoe_t$	0.0093	0.3269	-0.2662*	-0.0650	-0.0004
	(0.1792)	(0.2018)	(0.1402)	(0.1571)	(0.1650)
Cons	-8.3115***	2.3177	-0.3931	-0.6997	-0.6522
	(3.1560)	(4.5672)	(0.8725)	(0.9703)	(1.0177)
mu					0.5459**
					(0.2856)
eta					0.0401**
					(0.0177)
gamma					0.1665**
					(0.0911)
Year FE	NO	YES	NO	YES	NO
Country FE	YES	YES	NO	NO	NO

Note: ***, **, and * represent significance at a 1 per cent level, 5 per cent level, and 10 per cent confidence level, respectively. Figures in brackets are standard errors of estimates.

Source: Author's calculation.

As shown above, both FE and RE suggest that there only exists one lagged period. In column (1), the parameters of the second lagged period are not significant for both ln*Capin* and *d.R&Dinr*, with 0.225 and 0.298 p-values, respectively, while they are 0.106 and 0.686 in column (3), respectively. This implies that capacity investment, as well as growth in the proportion taken by R&D investment in total investment, does positively impact the newly installed capacity, not only in the current period but also in the following year.

Furthermore, parameters of del*lnwLcoe* are not significant in column (1), column (2), and column (4), while it is significant in column (3), but only at a 10 per cent confidence level. This means that the LCOE may not be a crucial variable in adding capacity. This is possible because of the fact that there has been a drastic reduction in LCOE in the renewable energy systems over the past decade as noted by IRENA. For example, the world average LCOE dropped dramatically, from 0.381 U.S. dollars per kilowatt-hour (USD/kWh) to 0.061 USD/kWh for solar photovoltaic (PV) power, from 2010 to 2019. However, we still would like to keep LCOE in the production frontier function as it is one of the core decision variables in capacity addition.

The result of SFA is shown in Table 2.2, column (5). First of all, the p-value of u_{it} proves that there exists significant technical inefficiency at a 5 per cent confidence level. According to equation (3), the coefficient *gamma* is calculated by $\gamma = \frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}$, which measures the extent to which the inefficiency term occupies the total deviation. Although the value of *gamma* is only 0.1665, its t-value provides a second piece of evidence for the significance of the inefficiency term. Besides, according to its 0.024 p-value, *eta* is significant at a 5 per cent confidence level, which demonstrates that there exists a time trend in technical inefficiency, and the positive sign shows that the technical inefficiency decreases over time. Overall, the SFA regression is considered as a proper estimation.

Not surprisingly, ln*Capin* is significant at a 1 per cent confidence level in both the current and one-lagged periods. The result suggests that a 1 per cent increase in capacity investment in the current period and last period will increase the newly added capacity by 0.50 per cent and 0.30 per cent, respectively. The significantly positive coefficient of ln*Lab* indicates that a 1 per cent increase in advanced labour force supply leads to a 0.25 per cent increase in total output.

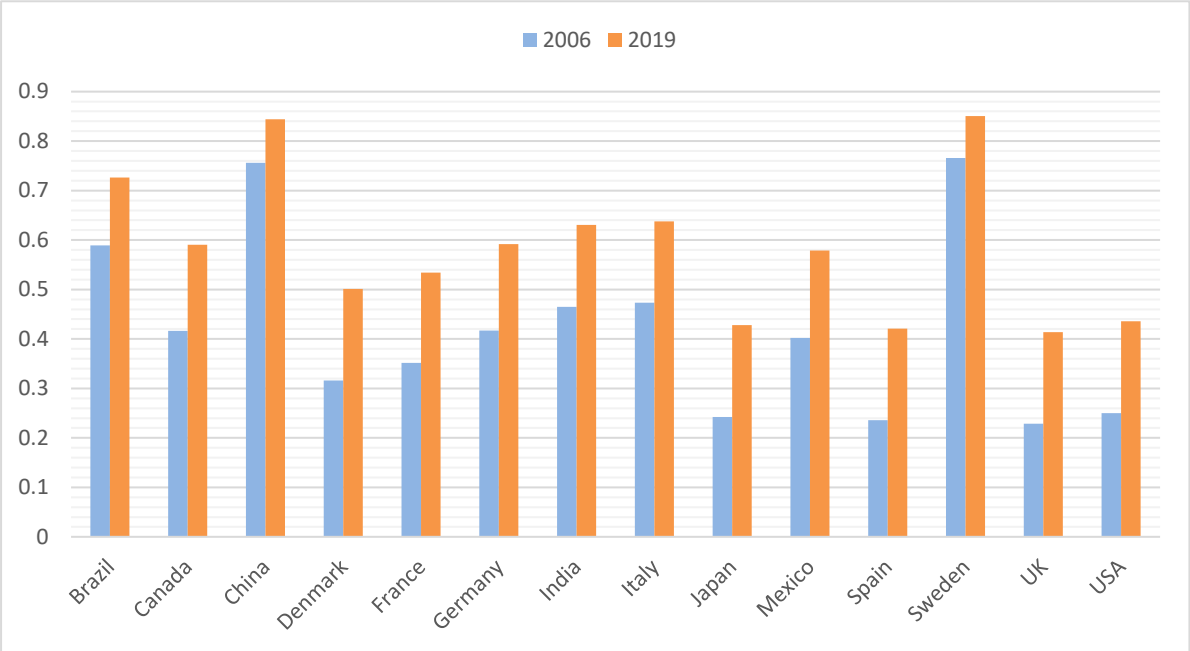
Similar to the results in the FE and RE regressions, *d.R&Dinr* is positively associated with the dependent variable, which means that the faster the R&D investment ratio in total investment grows, the more generation capacity can be installed, other factors remaining unchanged. This is an essential suggestion for governments, indicating that along with the dramatic increase in capacity investment over the past decade, they should pay more attention to relatively attracting or funding more R&D investment. The decisive role of R&D investment in the early stage may have a much more significant impact than expected.

The estimation of de*lnwLCOE* is not significant, although it has a negative sign. This finding strongly suggests that the considerable reduction in LCOE in recent years has not contributed to the growth in renewable energy power generation capacity.

2.5.2 Inefficiency decomposition results

Based on the estimation of the stochastic production frontier, technical efficiencies for each individual country can be calculated, which are shown in Figure 2.3.

Figure 2.3 Technical efficiency rates of capacity installation in 14 countries, 2006 and 2019



Source: Author's calculation.

Based on the estimation of technical inefficiency terms in each country, the result of the technical inefficiency decomposition model is shown in the following table (Table 2.3).

Table 2.3 Results of technical inefficiency decomposition model by FE and RE

Dependent variable: *mu*

Variables	FE	RE
Patent	-0.00151***	-0.00144***
	(0.00032)	(0.00032)
Im08b	-0.01156***	-0.01004***
	(0.00254)	(0.00235)
wLcoe	0.9341***	0.9483***
	(0.1417)	(0.1412)
Cons	0.78505***	0.76391***
	(0.03661)	(0.09264)
Country FE	YES	NO

Note: ***, **, and * represent significance at a 1 per cent level, 5 per cent level, and 10 per cent confidence level, respectively. Figures in brackets are standard errors of estimates.

Source: Author's calculation.

FE regression and RE regression generate similar results. The estimation of *Patent* corresponds to our expectation that it has a negative relationship with the technical inefficiency term at a 1 per cent significance level.

IM08 also has a significant negative coefficient, as predicted, which clearly declares that imports of renewable energy-related commodities reduce technical inefficiency in generation capacity installation. From my point of view, this effect is realised via three channels. Firstly, the development of the renewable electricity sector is varied and specialised in different countries. One country could enjoy the benefits of its trade partners' advantages and patents by importing parts and modules that are required in constructing plants and electricity generation. Secondly, although not covered by the data, trade in service may also play a crucial role. With respect to the increase in commodity trade, it is acceptable to consider that transboundary services delivered by

more skilled and qualified workers, such as designers, are also rapidly increasing, which would reduce the production inefficiency effectively. Finally, Li *et al*. (2020) argue that international knowledge spillovers have become an important input in the inventive process (p. 994), while Keller (2004) suggests that international trade in goods and services are two important carriers of international knowledge spillovers.

wLCOE also satisfies our prediction that it is positively correlated to technical inefficiency. This finding reveals that a reduction in LCOE would also reduce the technical inefficiency in capacity construction through particularly improving operational and maintenance activities. Thus, the result suggests that streamlining the operation and maintenance costs should not be neglected, which have implications for improving technical efficiency.

2.6 Conclusion and policy suggestions

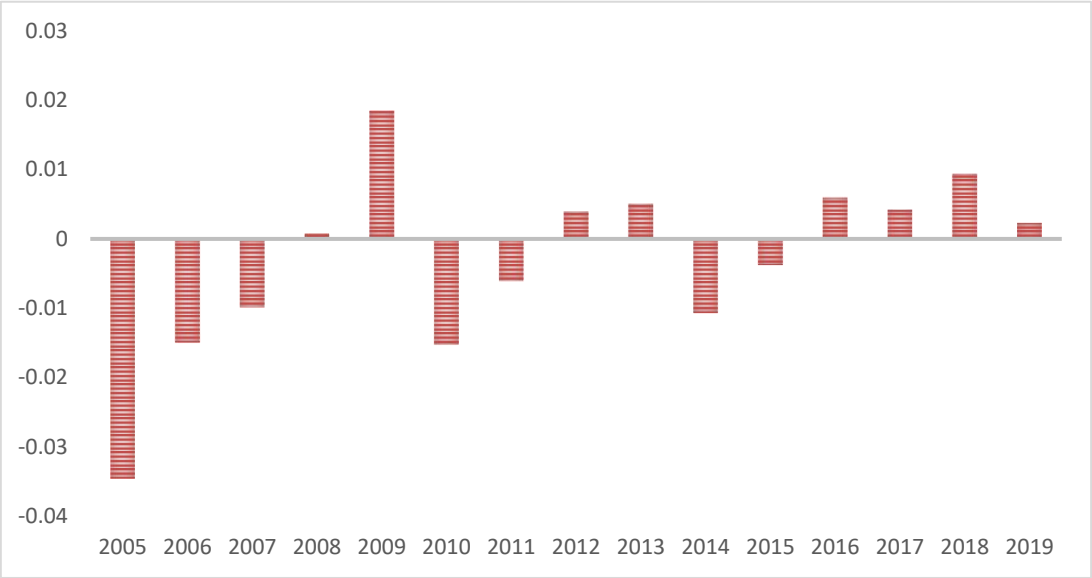
Renewable energy investment is crucial to achieve the SDGs and meet the Paris Agreement. However, as investment in renewable energy electricity generation has reached a significantly large scale, we should pay more attention to technical efficiency in transferring capacity investment into installed capacity.

This paper applied a two-stage SFA to measure and decompose the technical efficiency rate in 14 countries, using a panel data set from 2004 to 2019. Firstly, the empirical results show that significant technical inefficiency terms exist in all countries, and that technical inefficiency decreased over the sample period. This indicates that the improvement in technical efficiency also contributes to the increase in net added renewable energy power generation capacity, along with the surge in renewable energy investment.

Secondly, R&D investment is found to be more critical than just contributing to the decision-making stage. However, R&D's role seems to be underestimated by the current investment tendency. Figure 2.4 shows the net value of the R&D investment

ratio changes from 2005 to 2019. Compared with its previous period, the R&D investment ratio decreases approximately half of the time, while this paper suggests that a reduction in the R&D investment ratio would significantly impede increases in yearly installed capacity. Although the R&D investment ratio has shown an upward trend since 2015, the average value of its growth is smaller than 1 per cent.

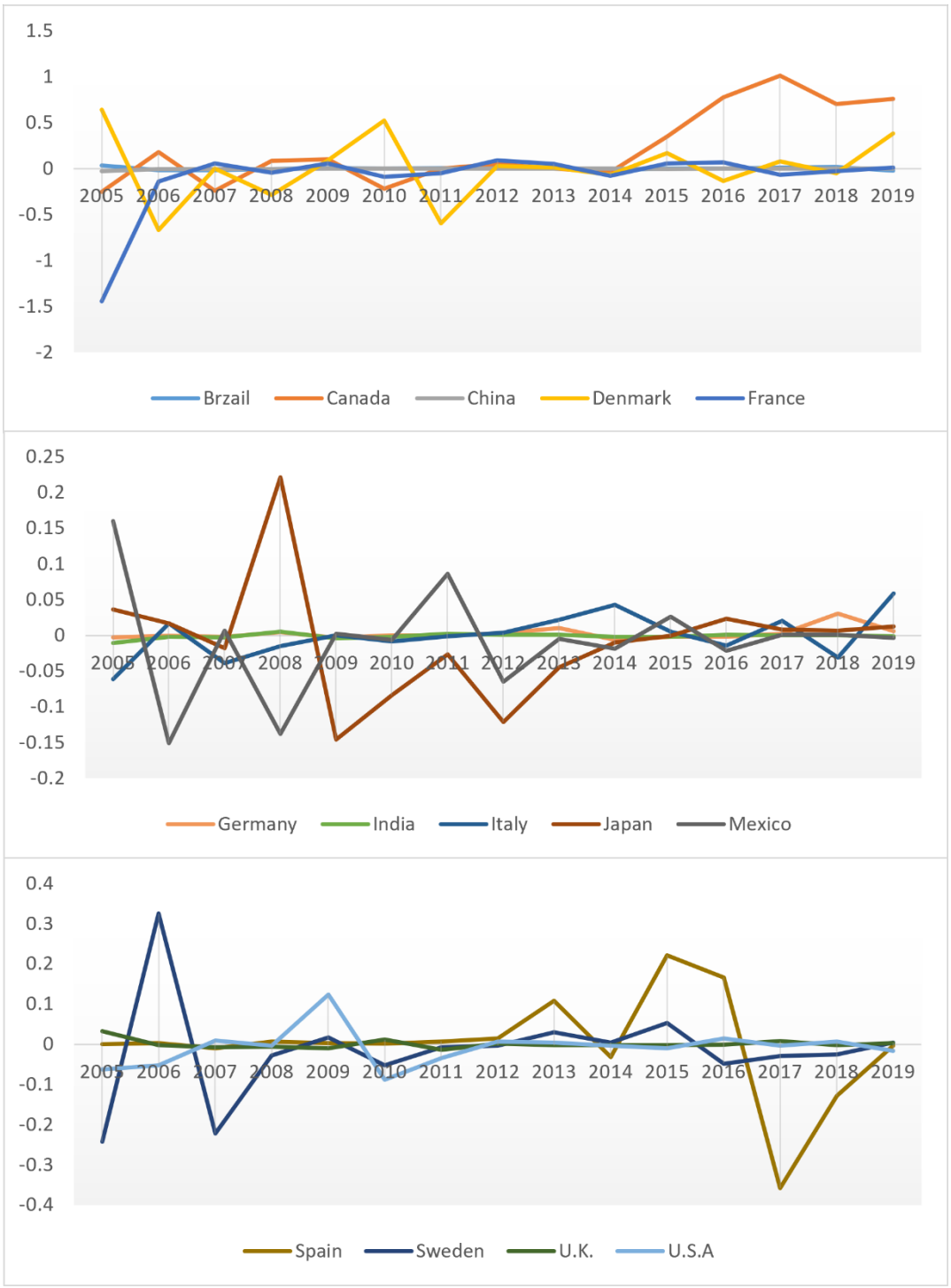
Figure 2.4 Growth of the R&D investment ratio, world total, 2005 to 2019



Source: Author's calculation.

Figure 2.5 presents the same data for all 14 countries. The R&D investment ratio fluctuates the most in Denmark, Japan, Spain, and Sweden. Canada shows the strongest upward trend in R&D investment in recent years. Although China, UK, and USA (except 2009 and 2010) display a steady status, they have negative growth rates in most of the past years.

Figure 2.5 Growth of the R&D investment ratio, country, 2005 to 2019



Source: Author's calculation.

Thirdly, based on the above estimations, this study further decomposed the technical inefficiency term to identify what determines it. The decomposition demonstrates that trade, as well as patents, in renewable energy-related goods has a significant impact on reducing the technical inefficiency term. This may be caused by international knowledge spillovers (learning by trading) and service trade. Overall, the more a renewable energy power project is integrated with the world, the more efficient the capacity construction process would be.

Finally, this paper also finds that cost reduction in renewable power generation does not significantly influence installed capacity, while it does improve technical efficiency.

Based on the findings, this paper proposes the following policy implications. First, technical improvement in renewable energy electricity generation capacity is equally significant as the increase in capacity investment. Currently, to rapidly develop the renewable energy sector, governments implement a package of policy instruments, from feed-in tariffs to tax reductions, to promote investment. However, policymakers should also pay attention to improving the technical efficiency in capacity investment. The traditional way is to advance relevant innovation, while governments can hardly control the process as the practice of government subsidies for 'promoting innovations efficiency is obviously unsustainable' (Lin & Luan 2020, p. 7). According to this study, an alternative solution is to integrate the renewable energy sector more with the world. For governments, they should create a better environment to facilitate trade in renewable energy-related commodities. The establishment of the Regional Comprehensive Economic Partnership (RCEP) is a good start, under which all member countries would gradually reduce tariffs on parts of renewable energy goods to zero. However, the depth and breadth of cooperation are far from satisfactory. More bilateral or multilateral agreements should be organised to accommodate more countries, more kinds of renewable energy-related goods, and more policy

instruments. For the developers and builders of energy projects, they should seek closer international or regional collaboration in the construction stage. For instance, decision-makers should consider importing more advanced components or modules used in the installation, of which the embodied techniques would considerably improve technical efficiency in capacity investment. Meanwhile, service trade, either independent of or embodied in commodity trade, should not be neglected. Both developed and developing countries could effectively improve foreign services by advancing their information and telecommunication technologies and participating more in global value chains (Thangavelu *et al.* 2018). In addition, local companies could also learn from the trading process, and develop their own knowledge for capacity installation.

Second, both public and private investors should pay more attention to R&D investment. Even though R&D investment is not directly associated with the construction phase, all investors should create a generous, and gradually increasing in the long run, budget for R&D investment in the planning stage.

Third, in the renewable energy sector, more efforts should be put into cultivating more experienced workers and management teams, to work on daily operations after energy projects are completed, to cut down on operational and maintenance costs. The accumulated experience will contribute to improving the technical efficiency of capacity investment in the construction phase.

This paper contains several limitations. Firstly, although this paper applied a panel data set at a country level, it only contains 224 observations. Secondly, it used renewable energy data, LCOE, and capital investment at an aggregate level due to data limitations. The adoption of industry-level data may give more precise and exciting results. Thirdly, because there is no available data to proxy the quality of the advanced labour force, this paper did not include this variable in the model, leaving room for future studies. Last, this paper did not consider policy instruments as a

determinant of technical efficiency, for example, whether environmental regulations or changes in government subsidy type have impacts on the technical efficiency term. Further studies are worth developing in this direction.

2.7 Appendix 2.I

$$LCOE = \sum_{t=1}^{n} \frac{I_t + M_t}{(1+r)^{t-1}} \Big/ \sum_{t=1}^{n} \frac{E_t}{(1+r)^{t-1}}$$

where *t* is designed lifetime, *i* is the capital investment in construction, *M* is operational and maintenance costs, *r* is the discount rate, and *E* is the designed electricity production over lifetime.

2.8 Appendix 2.II

Table 2.4 HS code of renewable energy commodities and descriptions

HS Code	Commodity
382450	Mortars and concretes; non-refractory
681091	Cement, concrete or artificial stone; prefabricated structural components for building or civil engineering, whether or not reinforced
700991	Glass mirrors; unframed, excluding rear-view mirrors for vehicles
700992	Glass mirrors; framed, excluding rear-view mirrors for vehicles
711590	Metal; precious or metal clad with precious metal, other than that of item no. 7115.10
730431	Iron or non-alloy steel (excluding cast iron); seamless, cold-drawn or cold-rolled, tubes, pipes and hollow profiles of circular cross-section
730441	Steel, stainless; cold-drawn or cold-rolled (cold-reduced), tubes and pipes of circular cross-section
730451	Steel, alloy (not stainless steel); seamless, cold-drawn or cold-rolled (cold-reduced), tubes, pipes and hollow profiles of circular cross-section
730820	Iron or steel; structures and parts thereof, towers and lattice masts
730900	Reservoirs, tanks, vats and similar containers; for any material (excluding compressed or liquefied gas), of iron or steel, capacity exceeding 300l, whether or not lined or heat insulated
741121	Copper; tubes and pipes, of copper-zinc base alloys (brass)
741122	Copper; tubes and pipes, of copper-nickel base alloys (cupro-nickel) or copper-nickel-zinc base alloys (nickel silver)
741129	Copper; tubes and pipes, of copper alloys (other than copper-zinc, copper-nickel base alloys (cupro-nickel) or copper-nickel-zinc base alloys (nickel-silver))
761090	Aluminium; structures (excluding prefabricated buildings of heading no. 9406) and parts of structures, n.e.c. in heading no. 7610, plates, rods, profiles, tubes and the like
761100	Aluminium; reservoirs, tanks, vats and similar containers, for material (not compressed or liquefied gas), of a capacity over 300l, whether or not lined, not fitted with mechanical/thermal equipment
830630	Photograph, picture or similar frames, mirrors; of base metal
840290	Boilers; parts of steam or other vapour generating boilers
840490	Boilers; parts of auxiliary plant, for use with boilers of heading no. 8402 and 8403 and parts of condensers for steam or other vapour power units
840510	Generators; producer gas, water gas, acetylene gas and similar water process gas generators, with or without their purifiers

840681	Turbines; steam and other vapour turbines, (for other than marine propulsion), of an output exceeding 40MW
840682	Turbines; steam and other vapour turbines, (for other than marine propulsion), of an output not exceeding 40MW
840690	Turbines; parts of steam and other vapour turbines
841011	Turbines; hydraulic turbines and water wheels, of a power not exceeding 1000kW
841012	Turbines; hydraulic turbines and water wheels, of a power exceeding 1000kW but not exceeding 10000kW
841013	Turbines; hydraulic turbines and water wheels, of a power exceeding 10000kW
841181	Turbines; gas-turbines (excluding turbo-jets and turbo-propellers), of a power not exceeding 5000kW
841182	Turbines; gas-turbines (excluding turbo-jets and turbo-propellers), of a power exceeding 5000kW
841199	Turbines; parts of gas turbines (excluding turbo-jets and turbo-propellers)
841280	Engines; pneumatic power engines and motors, n.e.c. in heading no. 8412
841290	Engines; parts, for engines and motors of heading no. 8412
841620	Furnaces; furnace burners, for pulverised solid fuel or gas, including combination burners
841919	Heaters; instantaneous or storage water heaters, non-electric, other than instantaneous gas water heaters
841931	Dryers; for agricultural products, not used for domestic purposes
841939	Dryers; for products n.e.c. in heading no. 8419, not used for domestic purposes
841960	Machinery; for liquefying air or gas, not used for domestic purposes
841989	Machinery, plant and laboratory equipment; for treating materials by change of temperature, other than for making hot drinks or cooking or heating food
841990	Machinery, plant and laboratory equipment; parts of equipment for treating materials by a process involving a change of temperature
842121	Machinery; for filtering or purifying water
842129	Machinery; for filtering or purifying liquids, n.e.c. in item no. 8421.2
843041	Boring or sinking machinery; self-propelled, n.e.c. in heading no. 8430
843049	Boring and sinking machinery; not self-propelled
847920	Machinery; for the extraction or preparation of animal or fixed vegetable fats or oils
850231	Electric generating sets; wind-powered, (excluding those with spark-ignition or compression-ignition internal combustion piston engines)
850239	Electric generating sets; (excluding those with spark-ignition or compression-ignition internal combustion piston engines), other than wind

	powered
851410	Furnaces and ovens; electric, for industrial or laboratory use, resistance heated
851420	Furnaces and ovens; electric, for industrial or laboratory use, functioning by induction or dielectric loss
851430	Furnaces and ovens; electric, for industrial or laboratory use, other than those functioning by induction, dielectric loss or resistance heated
851490	Furnaces, ovens and heating equipment; parts of the industrial or laboratory equipment of heading no. 8514
854390	Electrical machines and apparatus; parts of the electrical goods of heading no. 8543
854442	Insulated electric conductors; for a voltage not exceeding 1000 volts, fitted with connectors
854449	Insulated electric conductors; for a voltage not exceeding 1000 volts, not fitted with connectors
854460	Insulated electric conductors; for a voltage exceeding 1000 volts
890790	Floating structures; tanks, coffer-dams, landing stages, buoys and beacons
901380	Optical devices, appliances and instruments; n.e.c. in heading no. 9013 (including liquid crystal devices)
901580	Surveying equipment; articles n.e.c. in heading no. 9015, including hydrographic, oceanographic, hydrological, meteorological or geophysical instruments and appliances (excluding compasses)
902610	Instruments and apparatus; for measuring or checking the flow or level of liquids
902620	Instruments and apparatus; for measuring or checking pressure
902680	Instruments and apparatus; for measuring or checking variables of liquids or gases (excluding pressure or the flow and level of liquids and those of heading no. 9014, 9015, 9028 and 9032)
902690	Instruments and apparatus; parts and accessories for those measuring or checking the flow, level, pressure or other variables of liquids or gases (excluding those of heading no. 9014, 9015, 9028 or 9032)
902750	Instruments and apparatus; using optical radiations (UV, visible, IR), (other than spectrometers, spectrophotometers and spectrographs)
902830	Meters; electricity supply or production meters, including calibrating meters thereof
903020	Oscilloscopes and oscillographs
903031	Multimeters; for measuring or checking voltage, current, resistance or power, without a recording device
903032	Multimeters; for measuring or checking voltage, current, resistance or power, with a recording device
903033	Instruments and apparatus; for measuring or checking voltage, current,

	resistance or power, without a recording device (excluding multimeters)
903039	Instruments and apparatus; for measuring or checking voltage, current, resistance or power, with a recording device (excluding multimeters)
903190	Instruments, appliances and machines; parts and accessories for those measuring or checking devices of heading no. 9031

Chapter 3 The Trade Potential of Renewable Energy Commodities among RCEP Members[3]

Summary

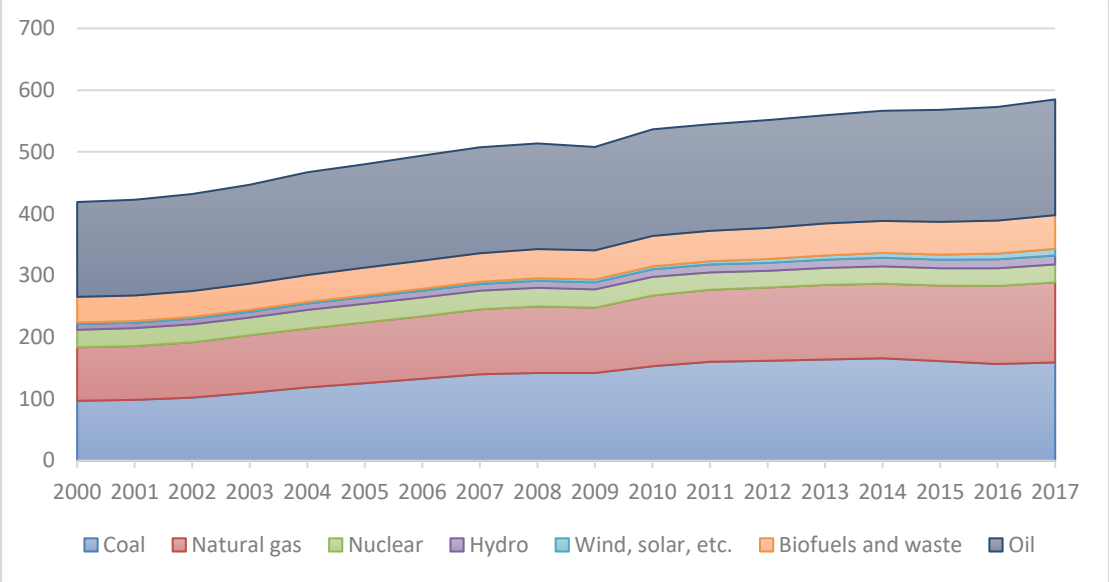
How effective the RCEP agreement could be in terms of boosting trade in renewable energy commodities between members remains unanswered in the literature. This paper applies a gravity model with a metafrontier approach to evaluate renewable energy commodities trade performance among selected RCEP countries. The metafrontier approach divides each country's total trade efficiency (TEM) into two components: each country's trade efficiency with respect to each group frontier and technology gaps between group frontiers and the metafrontier. First, the results confirm that countries with higher renewable energy goods export value adopt relatively more effective technology set in trade. Second, the highest TEM only scores 37.1 per cent, which illustrates that there are vast spaces for all RCEP countries to improve their trade efficiencies in renewable energy commodities within the region.

[3] A version of this chapter has been published by K. Kalirajan & Y. Liu, 'Regional cooperation in renewable energy trade: prospects and constraints', *Globalization of low-carbon technologies: the impact of the Paris Agreement*, Springer, 2017, pp. 459-478.

3.1 Introduction

With more than 160 countries ratifying the Paris Agreement, the Intended Nationally Determined Contributions (INDCs) officially turned into Nationally Determined Contributions (NDCs) at the UN Climate Change Conference in November 2017 (COP23). The Paris Agreement, which is by far the most significant international agreement in terms of climate change, requires all countries to set their own targets (NDCs) in line with the long-term goal of limiting the rise in the global temperature to well below 2 °C, and pursuing efforts to limit the increase to 1.5 °C. How well each government keeps their commitments regarding the NDCs will determine whether this goal is achieved. However, it looks like the implementation of climate actions is not on track.

Figure 3.1 World total energy supply by source, 2000 to 2016, Exajoule (EJ)

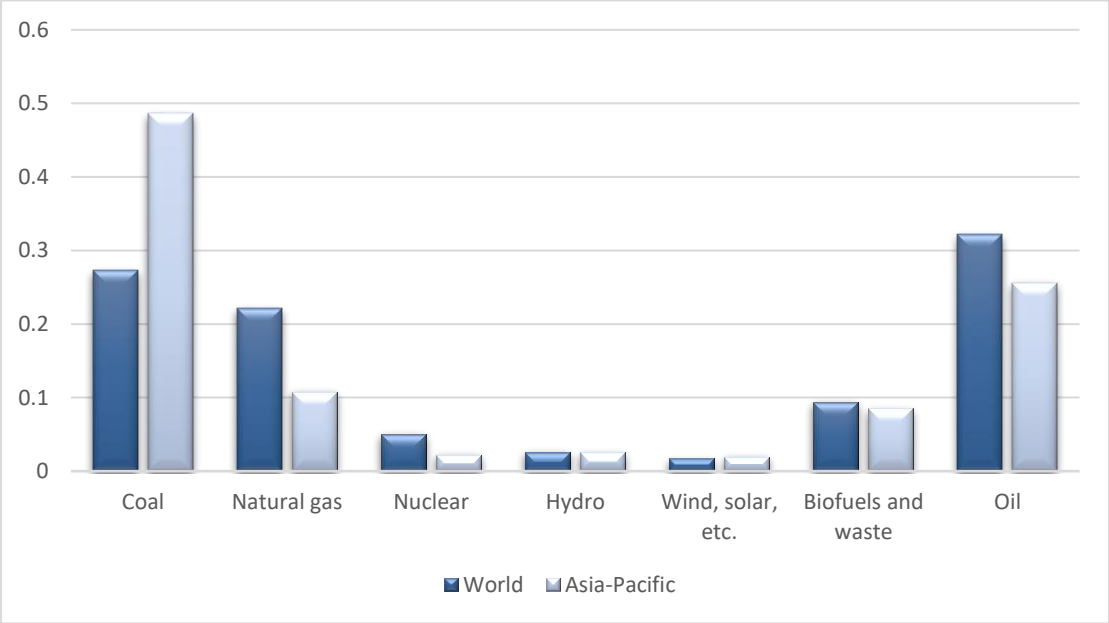


Source: International Energy Agency (IEA) World Energy Balances.

The Climate Change Performance Index (CCPI), established in 2005, evaluates the environment protection performance of 60 countries responsible for more than 90 per cent of global greenhouse gas emissions every year. In 2017, CCPI revised its methodology to better accommodate the assessment of all countries' performance

with respect to their NDCs. The CCPI 2017 report awards the top three positions in the overall ranking to no one, as 'even after the Paris Agreement came into force, no country has yet done enough to prevent the dangerous impacts of climate change' (p. 4). Also, as an important part of the Paris Agreement and the ultimate solution to greenhouse gas emissions, the development of the renewable energy sector falls behind schedule. Figure 3.1 shows the trend of the world's total energy supply, categorised by source, over the past two decades. Although the wind and solar energy supply in 2016 was approximately four times that of 2000, the proportion of renewable energy supply, including hydro and biomass power, only increased from 12.7 per cent to 13.5 per cent over the 16 years.

Figure 3.2 Asia-Pacific and world total energy supply by source, 2016, in proportion



Source: IEA World Energy Balances.

Given that Asia is a world leader in the manufacturing sector and the new driving force in world economic growth, the Asia-Pacific (APAC) region is experiencing rapidly growing demand for energy. Meanwhile, countries in this area are faced with

higher pressure to mitigate greenhouse gas emissions from fossil fuel use. As Figure 3.2 shows, despite APAC countries using proportionally less natural gas and oil resources compared with the world level, in 2016, the coal energy supply alone accounted for almost 50 per cent of the total energy supply. In addition, renewable energy, including hydropower and biofuels, only made up 12.9 per cent of the total number, which is even lower than the world level. Therefore, there are strong incentives and necessities for APAC countries to improve and sustain the development of renewable technologies to upgrade their energy systems and control greenhouse gas emissions, nationally and regionally. Renewable energy trade offers a unique, economically oriented policy solution to global climate challenges and will facilitate the greater deployment of efficient renewable energy technologies.

The effects of trade on the energy sector and emissions have been widely examined in the literature. Different studies show that results are complicated and depend on the specific situations, for example, the types of trade commodity and countries' current economic and energy structure (Halicioglu 2009; Dogan & Seker 2016). Nevertheless, it is commonly accepted that trade in renewable energy goods has positive impacts on reducing greenhouse gas emissions and the development of the renewable energy sector (Du *et al.* 2012; Sebri & Ben-Salha 2014; Jebli & Youssef 2015; Tiba *et al.* 2016). For exporting countries, increased trade in renewable energy commodities can facilitate energy industries expanding the production capacity. For importers, renewable energy trade provides access to more renewable energy resources with affordable costs, implying more renewable energy consumption. More importantly, the technology transfer embodied in trade will significantly and sustainably boost the future development of renewable energy in importing countries.

The establishment of the Regional Comprehensive Economic Partnership (RCEP) will be an opportunity to fill the increasing energy demand gap and practise trade in renewable energy products across APAC countries. Particularly, for those members

who lack the necessary renewable energy technology supply, RCEP offers a sustainable approach to gradually achieve their NDCs by creating and maintaining unconstrained renewable energy trade flows. However, one question that remains to be considered is whether trade in renewable energy goods has been sufficiently utilised, or to what extent the RCEP agreement can stimulate trade among member countries. The current literature leaves this area blank, and this study fills the research gap. Moreover, this study also examines whether all selected RCEP members share the same technology set (economic environment) in terms of exporting renewable energy commodities.

This study applies the gravity model in a metafrontier approach to evaluate the export potential of renewable energy commodities among RCEP member countries. This paper treats countries with different export levels differently. It is assumed that countries with higher trade values adopt a more efficient technology set for trade than countries with lower values in terms of exporting renewable energy goods. The total trade efficiency score consists of the technical efficiency with respect to group frontiers (TEG) and the meta-technology ratio (MTR), which are measured sequentially. Based on the empirical results, this study then proposes several political suggestions on how governments can improve export performance.

The rest of this paper is arranged as follows. Section 2 briefly reviews the literature on the gravity model, stochastic frontier analysis (SFA), and the metafrontier model. Section 3 introduces the theoretical work of the metafrontier model. Section 4 shows the empirical model and the data used in this paper, and Section 5 presents the results. The last section gives the conclusion.

3.2 Literature review

Since Tinbergen (1962) first introduced the gravity model into international trade, it has been widely used to analyse trade patterns, examine the effects of trade

influencers, and, more importantly, identify trade barriers and estimate trade potentials. When initially presented, the gravity model was criticised for lacking theoretical ground. Anderson (1979) is the first to theoretically derive the gravity model from the expenditure equation by assuming that commodities are differentiated among trading partners. Bergstrand (1985; 1989), Helpman (1987), and Deardorff (1995) make further contributions to the gravity model's theoretical foundation and demonstrate that the gravity model can be derived from various trade theories. Developed by a variety of empirical studies, a conventional gravity equation typically includes economic sizes (GDP), populations, geographical distance between trading partners, and other dummy variables or control indices used as the explanatory factors of trade flows. But it has also been suggested that the econometric specification of the gravity model is not consistent (Martinez-Zarzoso 2003; Armstrong 2007).

One significant problem of the conventional gravity model is that it does not perform well in explaining trade costs or trade resistances. Initially, it is assumed that there is no trade cost, or all trade costs can be represented by the distance variable in the gravity model (Deardorff 1995). However, McCallum (1995) finds that the trade volume between the U.S. and Canada is much less than the trade behind the border, which implies consequential resistances that reduce trade beyond the border. The literature has made considerable progress on the gravity model's specifications to precisely treat trade costs. More and more proxies and dummy variables, such as tariffs, exchange rates, shared borders, and common languages, are included in the gravity equation to measure trade costs 'beyond the border'. Nevertheless, there still exist some trade resistances that cannot be easily quantified, such as institutional barriers or infrastructure constraints; this paper describes these uncaptured resistances as the implicit trade cost. In the conventional gravity model, the implicit trade cost is assumed to be covered by the normally distributed random error with a zero mean. Kalirajan and Singh (2008) argue that this assumption is not in line with reality and may cause biased estimation. Anderson and van Wincoop (2004) also conclude that

international trade costs are very large and underestimated in the conventional gravity model, and that the measurement of trade costs needs to be improved.

One stream of application (Baldwin 1994; Nilsson 2000, *etc*.) is particularly related to the above concern, which uses the conventional gravity model to estimate the trade potentials of countries or regions. The term' trade potential' is defined as the expected trade volume which the gravity model calculates. As all implicit trade costs are classified into the random error and expected to be zero, the trade potential becomes a benchmark to judge whether the actual trade volume (as well as trade barriers) performs better or worse than the predicted volume. Nevertheless, the word 'potential' should refer to the maximum value that the trade could theoretically achieve if all implicit trade costs were eliminated.

The gravity model has employed the fixed effect model to control the effects of implicit trade costs and generate more accurate regression results. One assumption of this method is that all implicit trade costs are constant, which is likely to be inconsistent with reality. In addition, the fixed effect model also rules out the estimation of some explanatory variables that are unchanged over time, such as common border and language dummy variables.

SFA is an alternative solution that quantitively estimates the effects of the implicit trade cost and overcomes the limitations mentioned above. Proposed by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977), SFA measures technical inefficiency in the production process given different inputs and existing technology. The main idea of SFA is that it separates the error term into two parts, a non-negative term that represents the technical inefficiency in the production procedure and a random error that has the same meaning and distribution as in the conventional regression. Differences between the actual and predicted values, known as the production frontier, are caused by random disturbance and technical inefficiency. Therefore, the calculated production frontier refers to the theoretical-maximum output level if technical

inefficiency does not exist in production while there are still uncontrollable random shocks.

This concept can be adopted in the gravity model to improve the assessment of trade performance. In the stochastic frontier gravity model, implicit trade costs are treated as factors that reduce trade flows, not random errors as in the conventional model. Therefore, it is assumed that the implicit trade costs are embodied in the technical inefficiency term and strictly follow a non-negative distribution. Now, the value of the trade potential becomes the estimated production frontier and is redefined as the maximum trade volume that can be achieved theoretically if all implicit trade costs are removed. Meanwhile, the trade performance is represented by the ratio of actual trade volume to trade potential, also called the trade efficiency score, which indicates how well the trade potential has been realised. The judgement of the relative performance becomes simple and straightforward by comparing the trade efficiency scores of each objective after regression. Many studies (Drysdale *et al.* 2000; Kalirajan 2007; Ravishankar & Stack 2014, *etc*.) are aware of the advantages of SFA and have applied it to assess trade performance and quantify the implicit trade cost. Findings of these papers prove the assumption that the implicit trade cost is one of the main resistances that impede international trade. For example, Kalirajan (2007) uses SFA to examine the export performance of Australia to other 17 countries, and the paper finds that on average, Australia only realised 65 per cent of its export potential from 1992 to 1996, and the implicit trade cost accounted for 79 per cent of the variation.

Although technical efficiency levels can be compared within one regression or one group, comparison between different groups may not be meaningful. SFA assumes that different producers in the same group can have different inputs, but they all use the same kind of technology with different efficiency levels (or inefficiency levels). Therefore, comparisons across different groups are meaningless if producers in

different groups choose different technologies and have different production frontiers. For example, suppose that one study estimates the trade performance for Association of Southeast Asian Nations (ASEAN) countries within its region. The trade efficiency scores can be compared to identify which country performs the best, under the premise that all ASEAN members share the same production frontier. Similarly, European Union (EU) members' trade efficiency levels can be ranked within the region. However, the ASEAN members' efficiency scores cannot be directly compared with the EU members' scores, as they (very likely) have different production frontiers.

To make comparisons across groups practical and meaningful, Battese and Rao (2002) propose the concept of the metafrontier function, and Battese *et al.* (2004) and O'Donnell *et al.* (2008) further improve the metafrontier approach. It is assumed that a complete technology set exists for the production procedure, while each producer or group only has access to part of the complete technology set. Because of the inefficiency in technology selection, theoretically, a metafrontier envelops all groups' production frontiers. If one group is qualified with the complete technology set, its production frontier will coincide with the metafrontier. Therefore, the total technical inefficiency in production is decomposed into two components: the difference between actual production and each group's production frontier (the same as in SFA) and the difference between each group's production frontier and the metafrontier. Correspondingly, each group's total technical efficiency with respect to the metafrontier (TEM) is the product of the technical efficiency score with respect to its group frontier (TEG) and the meta-technology ratio (MTR), and the TEM is comparable between different groups. More details of the theoretical framework are discussed in the next section.

Battese *et al.* (2004) and O'Donnell *et al.* (2008) use two mathematical programming methods, linear programming (LP) and quadratic programming (QP), to calculate the

parameters of the metafrontier. However, Huang *et al.* (2014) point out that the parameters generated by mathematical programming methods do not have statistical properties. In addition, the LP and QP methods also ignore the effects of random shocks in the second step, which may cause biased estimations. Therefore, Huang *et al.* (2014) develop a new stochastic metafrontier regression (SMF) method to accommodate random shocks in the metafrontier function. By conducting two empirical regressions for the global agricultural industry and the hotel industry in Taiwan, they find that the MTR and TEM obtained from LP and QP are smaller than those from SMF and conclude that the SMF is preferable.

This paper applies the gravity model with the metafrontier approach and adopts all LP, QP, and SMF methods to measure the export performance of renewable energy commodities among RCEP members. It divides RCEP countries into two groups based on their export values, and thus two individual group production frontiers.

3.3 Theoretical framework

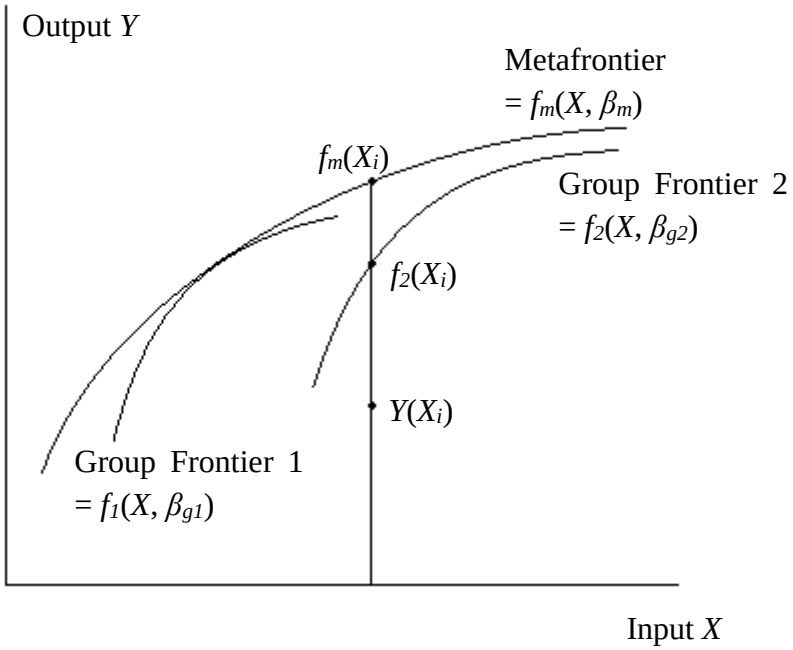
3.3.1 Illustration of the metafrontier approach

In SFA, technical efficiency, or production efficiency, represents how efficiently all inputs are used in the production process. It is assumed that a technical inefficiency term exists in the production function, which keeps the actual production value away from the production frontier. If several producers use the same technology in production, SFA can measure their technical inefficiency terms in one group or regression. The producer with a higher technical efficiency score, or a smaller technical inefficiency term, exploits the technology more efficiently, which means that the actual production is closer to the production frontier. However, if producers are assumed to be divided into different groups and each group uses different technologies, each producer's production efficiency must be calculated separately by each group. In this case, comparing technical efficiencies between different groups

cannot tell which producer enjoys the best production efficiency. For example, suppose that companies A and B use the same kinds of inputs to produce the same product, but they apply different technologies. If A has a 90 per cent technology efficiency score and B 65 per cent, the numbers only show that A and B realise 90 per cent and 65 per cent of their technology potential, respectively. However, one cannot say that A has better production efficiency than B.

Introduced by Battese and Rao (2002), Battese *et al.* (2004), and O'Donnell *et al.* (2008), the metafrontier approach is developed to generate meaningful comparisons of technical efficiencies between groups that produce the same products but employ different technologies. According to Battese and Rao (2002), the concept of the metafrontier is derived from the metaproduction function, which 'can be regarded as the envelope of commonly conceived neoclassical production functions' (p. 87; citing from Hayami & Ruttan, 1971, p. 46). It is assumed that a complete technology set exists for the production procedure, which is called the unrestricted technology set. However, because of a 'lack of economic infrastructure and/or other characteristics of the production environment' (O'Donnell *et al.* 2008, p. 232), each group of producers only has access to part of the unrestricted technology set, which is called the restricted technology set. As all restricted technology sets are subsets of the unrestricted technology set, the unrestricted set is more efficient than restricted sets when adopted in production. Theoretically, if one ideal producer can perfectly use the unrestricted technology set in production, its production frontier would envelop all other producers' frontiers, and this special frontier is called metafrontier. Therefore, the metafrontier approach decomposes each group's total technical inefficiency into two components: normal production inefficiency with respect to its group frontier, as in SFA, and the technology gap, represented by the difference between the group frontier and the metafrontier. Figure 3.3 shows how the metafrontier works simplified with two individual groups.

Figure 3.3. Metafrontier model illustration



The above figure shows that the metafrontier model consists of individual group frontiers and the metafrontier. Group frontiers are drawn from each group's stochastic production function ($f_1(.)$ and $f_2(.)$), and metafrontier is drawn from the metafrontier function $f_m(.)$. According to Battese *et al.* (2004), the metafrontier function is defined as a deterministic parametric frontier with the condition that the metafrontier values are no smaller than the values of any deterministic group frontiers. In addition, Battese *et al.* (2004) also assume that the metafrontier function is 'a smooth function and not a segmented envelope of the stochastic frontier functions for the different groups' (p. 93). Suppose that an individual company i adopts a restricted technology set from the second group, and $Y(Xi)$ is actual production with the input X_i. If i can overcome all technical inefficiencies under the restricted technology set, it would produce at the group frontier with the predicted value $f_2(Xi)$. Therefore, the distance between $Y(Xi)$ and $f_2(Xi)$ represents the production inefficiency with respect to group frontier 2. Further, if i can advance its technology from the restricted technology set to the unrestricted technology set, its predicted production value would increase from $f_2(Xi)$ to $f_m(Xi)$. The distance between $f_2(Xi)$ and $f_m(Xi)$ represents the inefficiency from

the technology gap. Overall, the distance between $Y(Xi)$ and $f_m(Xi)$ is the total technical inefficiency with respect to the metafrontier, which can be compared between producers from the same or different groups.

The calculation process is also divided into two steps. First, data on each producer's inputs and actual output is used to estimate the coefficients of each group's production function (β_{g1} and β_{g2}) via SFA, respectively. Second, using the calculated group frontiers from the first step to measure the coefficients of the metafrontier function (β_m).

3.3.2 Group frontiers by SFA

Assume that there are *I* producers and all producers are divided into *K* groups based on their technology sets. Each producer's output is determined by its stochastic production function respectively:

$$Y_{it} = f_k(X_{it}, \beta_k) \exp\left(-u_{it}^k + v_{it}^k\right) \quad (1)$$

$$i = 1,2, \dots, I;\ k = 1,2, \dots, K$$

According to equation (1), if the *i*th producer belongs to the *k*th group, it can produce *Y* with a vector of inputs *X* at time *t*. β_k is a vector of coefficients of the *k*th group production function. u_{it}^k represents the technical inefficiency in the production procedure, and v_{it}^k is the random shock. A natural logarithm transformation is performed to transform equation (1) into a linear expression:

$$\ln Y_{it} = \ln f_k\left(X_{it}, \beta_k\right) - u_{it}^k + v_{it}^k \quad (2)$$

Conventionally, the production function $f_k(.)$ is presumed to be log-linear, such as the Cobb-Douglas production function. According to the definition of the technical inefficiency term, u_{it}^k is strictly non-negative and assumed to follow a truncated normal distribution, $u_{it}^k \sim N^+(u^k, \sigma_{u^k}^2)$. The random error follows a normal

distribution independently and identically, $v_{it}^{k} \sim N(0, \sigma_{v^k}^2)$. SFA uses a maximum likelihood method on equation (2) to estimate each group production function's parameters.

The value of the group frontier is the theoretical production value if the producer could fully utilise its restricted technology set, which means there is no technical inefficiency in production. The ratio of the actual output to the predicted group frontier represents the technical efficiency of each producer with respect to its group frontier (TEG). Based on the regression results of each group production function, the *i*th producer's TEG can be expressed as

$$TEG_{it} = \frac{Y_{it}}{E(Y_{it}|u_{it}^{k}=0, X_{it})} = \frac{Y_{it}}{f_k(X_{it},\beta_k)\exp(v_{it}^{k})} = \exp(-u_{it}^{k}) \quad (3)$$

A more comprehensive derivation of TEG can be found in the previous chapter.

3.3.3 Metafrontier by LP and QP

Similar to group frontiers, the value of the metafrontier is determined by the metafrontier function. Battese *et al.* (2004) define the metafrontier function for all *I* producers, no matter which groups they belong to, as

$$Y_{it}^{m} = f_m(X_{it}, \beta_m) \quad (4)$$

where $f_m(.)$ is assumed to have the same expression as $f_k(.)$, β_m is a vector of the metafrontier function's parameters, and Y_{it}^{m} is the theoretical maximum output if producer-*i* fully comprehends the unrestricted technology set, following the restriction that

$$f_m(X_{it}, \beta_m) \geq f_k(X_{it}, \beta_k) \quad (5)$$

To connect the metafrontier with the actual output, the authors rewrite equation (1) as

$$Y_{it} = \exp(-u_{it}^{k}) \times \frac{f_k(X_{it},\beta_k)}{f_m(X_{it},\beta_m)} \times f_m(X_{it},\beta_m)\exp(v_{it}^{k}) \quad (6)$$

In equation (6), the first term on the right-hand side is the *i*th producer's TEG, as shown in equation (3). Battese *et al.* (2004) and Huang *et al.* (2014) define the second term, the ratio of the *k*th group frontier to the metafrontier, as the technology gap ratio, which represents how close the *k*th group frontier is to the metafrontier. However, O'Donnell *et al.* (2008) point out that the name of the technology gap ratio can be confusing, as a higher ratio means a smaller technology gap. They rename the ratio as the meta-technology ratio (MTR), which is also used in this paper:

$$MTR_{it}^{k} = \frac{f_k(X_{it},\beta_k)}{f_m(X_{it},\beta_m)} \quad (7)$$

Note that although producers in the same group share the same group frontier, producers that commonly have various sets of input would produce on different points relative to the group frontier. Therefore, MTR is sensitive to each producer's identity.

Similar to the TEG, Battese *et al.* (2004) define technical efficiency with respect to the metafrontier (TEM) as the ratio of actual output to the predicted metafrontier with the corresponding random shock from production:

$$TEM_{it} = \frac{Y_{it}}{f_m(X_{it},\beta_m)\exp(v_{it}^{k})} \quad (8)$$

Combining equations (3), (6), (7), and (8), each producer's TEM can be expressed as the product of its TEM and MTR:

$$TEM_{it} = TEG_{it} \times MTR_{it}^{k} \quad (9)$$

Battese *et al.* (2004) and O'Donnell *et al.* (2008) introduce LP and QP methods to generate β_m. LP constructs an objective function that minimises the sum of absolute deviations of the metafrontier to group frontiers, expressed as

$$\min \sum_{i=1}^{I} \sum_{t=1}^{T} \left| \ln f_m(X_{it}, \beta_m) - \ln f_k\left(X_{it}, \widehat{\beta_k}\right) \right|, s.t. \quad (10)$$

$$\ln f_m(X_{it}, \beta_m) \geq \ln f_k\left(X_{it}, \widehat{\beta_k}\right) \quad (11)$$

where $\widehat{\beta_k}$ is the estimation of β_k from the first step. Equation (11) ensures the assumption that the metafrontier envelops all group frontiers. Parameters of the metafrontier function can be obtained by solving the above linear optimisation problem.

Similarly, QP solves a quadratic optimisation problem, of which the objective function minimises the sum of squares of the deviations, expressed as

$$\min \sum_{i=1}^{I} \sum_{t=1}^{T} \left[\ln f_m(X_{it}, \beta_m) - \ln f_k\left(X_{it}, \widehat{\beta_k}\right) \right]^2, s.t. \quad (12)$$

$$\ln f_m(X_{it}, \beta_m) \geq \ln f_k\left(X_{it}, \widehat{\beta_k}\right) \quad (11)$$

Compared with LP's calculation, producers with lower MTR takes a more important position in the calculation of QP.

3.3.4 Metafrontier with SMF

Huang *et al.* (2014) illustrate two major drawbacks in LP and QP. Firstly, the calculated parameters have no statistical meanings as the derivation logic is purely algebraic. More importantly, they indicate that the mathematical programming methods are confounded by random shocks. When calculating parameters of the metafrontier function, LP and QP use the predicted value of group frontiers from the first step, while Huang *et al.* (2014) argue that the adoption of estimated group frontiers neglects the effect of the errors between $f_k(X_{it}, \beta_k)$ and $f_k\left(X_{it}, \widehat{\beta_k}\right)$. Therefore, a random error term should be considered when estimating $f_m(X_{it}, \beta_m)$ to cover this disturbance.

This paper analyses this issue from a different angle. As the distance between group frontiers and the metafrontier is caused by inefficiency in choosing a technology set, their relationship can be considered the same as the relationship between the actual output and the group frontier. Values of each group frontier can be treated as outputs of a stochastic production process which is determined by the metafrontier function and contains a technical inefficiency term. Thus, the group frontiers' 'production process' can be expressed as:

$$f_k(X_{it}, \beta_k) \exp(v_{it}^k) = f_m(X_{it}, \beta_m) \exp(-u_{it}^m + v_{it}^m) \quad (13)$$

where the left-hand side represents the group frontier drawing from equation (3), u_{it}^m is the inefficiency term in technology selection, namely the technology gap, and v_{it}^m is the random error in the 'production process'. Therefore, u_{it}^m is also assumed to be strictly non-negative and follows a truncated normal distribution, $u_{it}^m \sim N^+(u^m, \sigma_{u^m}^2)$, and v_{it}^m follows a normal distribution, $v_{it}^m \sim N(0, \sigma_{v^m}^2)$. Then, as the MTR shows the extent to which each restricted technology set exploits the unrestricted technology set, its expression is modified as:

$$MTR_{it}^k = \frac{f_k(X_{it}, \beta_k) \exp(v_{it}^k)}{f_m(X_{it}, \beta_m) \exp(v_{it}^m)} = \exp(-u_{it}^m) \quad (14)$$

Correspondingly, TEM is rectified as:

$$TEM_{it} = \frac{Y_{it}}{f_m(X_{it}, \beta_m) \exp(v_{it}^m)} \quad (15)$$

However, TEM is still the product of TEG and MTR, as the new decomposition of equation (1) shows that:

$$Y_{it} = \exp(-u_{it}^k) \times \frac{f_k(X_{it}, \beta_k) \exp\left(v_{it}^k\right)}{f_m(X_{it}, \beta_m) \exp\left(v_{it}^m\right)} \times f_m(X_{it}, \beta_m) \exp(v_{it}^m) \quad (16)$$

Recalling that both $f_k(.)$ and $f_m(.)$ are log-linear, equation (13) is transformed as:

$$\ln(f_k(X_{it}, \beta_k) \exp(v_{it}^k)) = \ln f_m(X_{it}, \beta_m) - u_{it}^m + v_{it}^m \quad (17)$$

SFA is used to estimate the parameters of the metafrontier function in the second step, equation (17), and Huang *et al.* (2014) call this method SMF. In practice, the value of the dependent variable in equation (17) comes from the estimation result in the first step, $f_k(X_{it}, \widehat{\beta_k})$ and $\widehat{v_{it}^k}$.

Compared with LP and QP, SMF embodies a random error in the second step and clarifies the effects of each error term in both steps. As shown in equation (4), the metafrontier function used in LP and QP does not hold a random error. In addition, equation (3) presents that, when calculating the TEG, the value of group frontiers in LP and QP has cooperated with the random error $\exp(v_{it}^k)$. However, when defining MTR, equation (7) does not include this random shock, as well as equations (10) and (12). SMF solves this conflict in LP and QP by redefining MTR and the metafrontier.

To sum up, this study uses SFA in the first step to estimate the gravity equation and countries' TEG for each group, respectively. Secondly, gathering the estimation results for all groups from the previous step, this study applies LP, QP, and SMF to estimate the metafrontier and MTRs, and it compares the results between different methods to analyse the effect of the attendance of v_{it}^k. Finally, the estimated comparable trade efficiency score with respect to the metafrontier is calculated as

$$\widehat{TEM_{it}} = \widehat{TEG_{it}} \times \widehat{MTR_{it}^k} \tag{18}$$

3.4 Model specification and data description

This paper applies the gravity model with the metafrontier approach to evaluate the export performance of renewable energy goods in RCEP countries, assuming that different countries may have different technology sets and trade frontiers in terms of exports. The specific gravity equation used in regression is expressed as:

$$\ln TV_{ijt} = \beta_0^k + \beta_1^k \ln Exgdp_{it} + \beta_2^k \ln Imgdp_{jt} + \beta_3^k \ln Expop_{it} + \beta_4^k \ln Impop_{jt}$$

$$+\beta_5^k \ln Dist_{ijt} + \beta_6^k \ln Taf_{jt} + \beta_7^k \ln ER_{ijt} + \beta_8^k CSL_{ijt} + \beta_9^k Time_t - u_{ijt}^k + v_{ijt}^k \quad (19)$$

In the above equation, TV_{ijt} represents the export value of renewable energy commodities from export country *i* to import country *j* at time *t*, and *k* indicates which group the exporter belongs to. *Exgdp* and *Imgdp* are real GDPs in exporter and importer countries, respectively, which are predicted to have a positive sign. According to Martinez-Zarzoso (2003), the population in exporting countries, *Expop*, is expected to have a mixed effect on exports, the same as its counterpart *Impop*. *Dist* is the geographic distance between capital cities of two trading partners and should have a negative sign. *Taf* is the tariff that the importer country imposes on trade, and it should reduce the export value as a trade cost. *ER* is the relative exchange rate, of which a higher value means that the exporter's currency appreciates relative to the importer's currency. Therefore, a higher *ER* would relatively increase the export price and reduce the trade volume, but the total effect depends on the elasticity of renewable energy goods. A proxy for a common spoken language between two countries *CSL* is included in the regression and expected to have a positive sign. *Time* is a time trend variable that captures the time effect. u_{ijt}^k and v_{ijt}^k are the technical inefficiency term and the random error in each group production function, for which the characteristics are discussed in the previous section. The metafrontier function used in SMF has the same expression as equation (19), while it substitutes the dependent variable $\ln TV_{ijt}$ with the estimated values of the group production frontiers.

Because of data limitations, the panel data set in this paper consists of data from 11 RCEP members between 2006 to 2014, and exporters are divided into two groups based on their export values. Group 1 includes countries with relatively higher export values, which are China, Japan, South Korea, Malaysia, and Singapore, while Australia, Indonesia, New Zealand, Philippines, Thailand, and Vietnam are included

in the second group. Group 1 has 450 observations, and Group 2 has 522 observations as the Philippines' and Vietnam's export data to New Zealand are omitted. The export data is obtained from the United Nations Comtrade Database (UN Comtrade), and the HS code of renewable energy commodities is listed in Appendix 3.I. Real GDP, population, and exchange rates are collected from the World Bank database. Data on distances and the index of common spoken language are taken from CPEII. Tariff rates of each renewable energy commodity are obtained from the tariff download facility, and a weighted average ratio is used in the regression. The following Table 3.1 shows the statistical summary of the data set, while only exporters' GDP and population data is presented as importers' data is almost the same. To avoid the $\ln(0)$ problem, the variable $\ln Taf_{it}$ is calculated as $\ln Taf_{it} = \ln(Taf_{it} + 1)$.

Table 3.1 Data set statistical summary

Variable	Unit	Mean	Std. Dev.	Min	Max
Group 1					
TV	$million	818.6661	2518.903	.2376	22443.64
GDP	$billion	2620.013	2849.899	147.797	10354.8
Pop	million	309.6003	516.3194	4.4014	1364.27
Dist	kilometre	4241.317	2729.887	315.5433	11041.03
ER	ratio	713.9561	2358.361	0.00086	16729.33
Taf	per cent	3.0118	2.2008	0	7.3344
CSL	ratio	0.1281	0.2057	0	0.6958
Group 2					
TV	$million	27.7905	101.408	0.00099	1501.027
GDP	$billion	550.7	404.4255	66.3717	1563.95
Pop	million	85.7017	78.3247	4.1846	254.4548
Dist	kilometre	4903.627	3006.154	886.1407	11041.03
ER	ratio	870.1148	3190.353	0.00005	21565.52
Taf	per cent	3.0594	2.3867	0	7.3344
CSL	ratio	0.1312	0.2393	0	0.9506

Source: Author's calculation.

3.5 Results and discussion

3.5.1 Group frontiers results

In the first step, this paper uses Stata to perform SFA to estimate the stochastic production function parameters for two groups, respectively. To test the assumption that the two groups adopt different technology sets for exporting renewable energy goods, it also estimates the production function, which pools all countries' data together. Table 3.2 presents the regression results.

Table 3.2 SFA regression results for Group1, Group2, and the pooled data

Dependent variable: ln *TV*

Variables	Group 1	Group 2	Pooled Data
ln *Exgdp*	0.8514***	0.4370	1.1723***
	(0.1835)	(0.2793)	(0.1456)
ln *Imgdp*	0.3694***	1.0533***	0.6561***
	(0.1398)	(0.1755)	(0.1220)
ln *Expop*	0.0066	0.4517**	-0.0757
	(0.1516)	(0.2063)	(0.1148)
ln *Impop*	0.4450***	-0.4266**	-0.1357
	(0.1425)	(0.1756)	(0.1406)
ln *Dist*	-1.0364***	-1.5057***	-1.7890***
	(0.1627)	(0.3280)	(0.2698)
ln *ER*	0.0165	0.0429	-0.0331
	(0.0324)	(0.0458)	(0.0325)
ln *Taf*	-0.1749	-0.1159	-0.0307
	(0.1738)	(0.2380)	(0.1781)
CSL	0.1838	0.5506	-0.1379
	(0.6210)	(0.8864)	(0.6120)
Time	-0.0966***	-0.0507	-0.0121
	(0.0373)	(0.0563)	(0.0249)
Constant	-11.5998***	-9.7299	-11.3747**
	(4.0527)	(8.1251)	(4.6189)
mu	0.9132***	1.4326***	1.3398***
	(0.2171)	(0.4449)	(0.2666)
eta	0.0533***	0.0133	-0.0081
	(0.0124)	(0.0177)	(0.0069)
gamma	0.6480***	0.5323***	0.8575***
	(0.0667)	(0.0720)	(0.0332)
Log-likelihood	-475.3016	-832.9853	-1426.5018

Note: ***, **, and * represent significance at a 1 per cent, 5 per cent, and 10 per cent confidence level, respectively. Figures in brackets are standard errors of estimates.

Source: Author's calculation.

Before generating each country's TEG, several hypotheses need to be examined. First of all, it is necessary to confirm the presence of the technical inefficiency term in both group production functions, which is determined by the coefficient *gamma*. *Gamma* is

the ratio of the variance of the technical inefficiency term to the total variance of both error terms, which is expressed as $\gamma = \frac{\sigma_u^2}{\sigma_u^2+\sigma_v^2}$ and takes a value between 0 and 1. A significant *gamma* proves that the inefficiency term causes part of the total deviation significantly. As shown in Table 3.2, both regressions have a significant *gamma* at 1 per cent confidence level, which means that it is appropriate to adopt SFA in the regressions to measure the parameters for group production functions. In addition, estimations of u_{ijt}^k in both regressions provide the second piece of evidence that all countries' exports in renewable energy commodities have trade inefficiency issues.

Secondly, it is essential to examine whether the two groups have different technology sets and production frontiers. If all countries' exports share the same technology set, there would be no need to further measure the metafrontier and TEMs as TEGs would be directly comparable. Following Battese *et al.* (2004), this paper uses a likelihood-ratio (LR) test for the null hypothesis that two groups have the same stochastic frontier. The *LR* statistic is calculated by:

$$LR = -2\{\ln[L(H_0)/L(H_1]\} = -2\{\ln[L(H_0)] - \ln[L(H_1)]\} \qquad (20)$$

where $\ln[L(H_0)]$ is the value of the log-likelihood function, which uses pooled data from all countries, and $\ln[L(H_1)]$ is the sum of the values of the log-likelihood function that estimates the group production frontiers. The *LR* statistic follows a Chi-square distribution, and the degrees of freedom are the difference between the number of parameters estimated under H_1 and H_0, which are 12 in this case. The bottom line in Table 3.2 displays the values of log-likelihood functions, and the LR statistic is 236.4298 and has a 0 p-value, significantly rejecting the null hypothesis. Thus, countries in different groups have different restricted technology sets, and it is appropriate to estimate each group's frontier separately.

Comparing the regression results between Group 1 and Group 2, the absolute values

of the corresponding coefficients are significantly different. However, the estimated parameters in Group 1 have the same sign as their counterparts in Group 2 and are in line with the expectations, except for the variable *Impop*. The population in importing countries has a significant and positive impact on exports in the first group, but a negative one in the second group. This paper explains this difference by the different properties of renewable energy commodities from different countries. It is reasonable to assume that export commodities from higher volume countries probably enjoy some kinds of comparative advantages, such as lower prices, better reputation, and more advanced technology. Therefore, when the market size in importing countries increases, individuals and companies would prefer products from the first group more than the second group.

The coefficients of *Taf* in both regressions are negative but not statistically significant even at a 10 per cent confidence level. This implies that reducing tariff rates for renewable energy commodities would promote export values, but the effect is insignificant. The coefficient *eta* indicates whether technical inefficiency changes overtime or not. The positive values of *eta* in both group regressions means that the u_{ijt}^{k} is decreasing over the estimation period, or trade efficiency scores are improved, in the two groups. However, the changes are significant in Group 1 but not significant in Group 2.

TEGs are calculated based on the group regression results, and each country's average TEG is shown in Table 3.3.

Table 3.3 Estimations of the technical efficiency scores with respect to the group frontiers

Group 1	TEG	Group 2	TEG
China	0.3643	Australia	0.3322
Japan	0.3506	Indonesia	0.1779
South Korea	0.3836	New Zealand	0.1830
Malaysia	0.2535	Philippine	0.1908
Singapore	0.4302	Thailand	0.4644
		Vietnam	0.2181
Total mean	0.3564	Total mean	0.2611

Source: Author's calculation.

In Group 1, Singapore performs the best in exporting renewable energy commodities with the highest TEG of 0.4302, while Malaysia has the lowest TEG of 0.2535. The remaining three countries' TEG estimations lie between 0.3506 to 0.3836. In Group 2, Thailand's export efficiency is considerably higher than the other countries with a value of 0.4644, followed by a value of 0.3322 in Australia. The other four countries' TEG estimations are approximately around 0.19. The total means of TEGs in Group 1 and Group 2 are 0.3564 and 0.2611, respectively.

Again, the results of TEGs are not comparable across the two groups. The next step is to generate comparable TEMs by calculating MTRs for all countries together.

3.5.2 Metafrontier results

The estimations of all countries' theoretical maximum export values with respect to their group frontiers from the first step are used to measure the metafrontier function. This paper uses the R programming language to solve the LP and QP problems with respect to equations (10) and (12), respectively, and it uses Stata to run the SMF estimation with respect to equation (19). Table 3.4 lists the estimated coefficients of

the metafrontier function for LP, QP, and SMF.

Table 3.4 Estimations of the metafrontier function

Dependent variable: Estimations of the values of the group production frontiers			
Variables	LP	QP	SMF
ln *Exgdp*	0.8324	0.8634	0.5581***
			(0.0127)
ln *Imgdp*	0.3657	0.4208	0.7363***
			(0.0144)
ln *Expop*	0.0540	0.0779	0.4401***
			(0.0174)
ln *Impop*	0.4063	0.3731	-0.0323
			(0.0201)
ln *Dist*	-1.2362	-1.2409	-1.3623***
			(0.0239)
ln *ER*	0.0178	0.0204	0.0337***
			(0.0037)
ln *Taf*	-0.2052	-0.1807	-0.1455***
			(0.0158)
Csl	0.3909	0.4708	0.5085***
			(0.0685)
Time	-0.0929	-0.1021	-0.1379***
			(0.0023)
Constant	-9.3135	-11.4153	-8.6987***
			(0.4065)
mu			1.9091***
			(0.1493)
eta			0.0295***
			(0.0005)
gamma			0.9987***
			(0.00025)
Log-likelihood			1225.4878

Note: ***, **, and * represent significance at a 1 per cent, 5 per cent, and 10 per cent confidence level, respectively. Figures in brackets are standard errors of estimates.

Source: Author's calculation.

As analysed in the group regression results, the estimation of *gamma* shows significant technical inefficiency (a technology gap) between the metafrontier and the

group frontiers. The ratio $1-\gamma=\frac{\sigma_v^2}{\sigma_u^2+\sigma_v^2}$, which has the exact opposite meaning to γ that measures the effect of random error on the total deviation, is used to examine the presence of the random error in the metafrontier function. The value of this ratio is 0.0013 in the SMF regression result but statistically significant at a 1 per cent level, which implies that a significant random error exists, even though its magnitude may be very small. This result is consistent with the conclusion in the work of Huang *et al.* (2014). Table 3.5 reports the estimated MTRs and TEMs based on the LP, QP, and SMF estimation results, respectively.

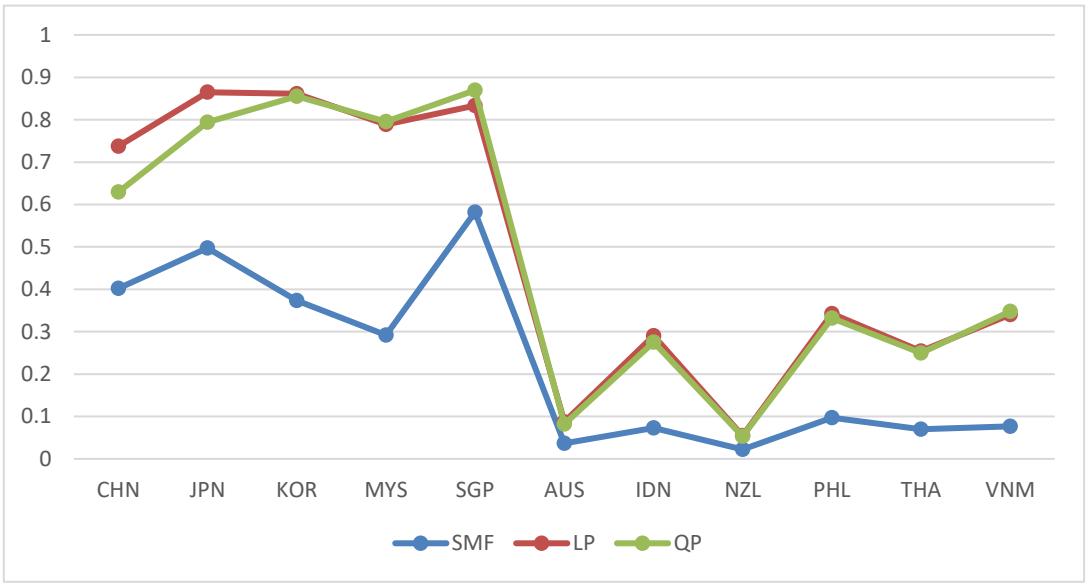
Table 3.5 Estimations of the meta-technology ratios and the technical efficiency scores with respect to the metafrontier

	LP estimates		QP estimates		SMF estimates	
Group 1	MTR	TEM	MTR	TEM	MTR	TEM
China	0.7376	0.2667	0.6292	0.2262	0.4020	0.1401
Japan	0.8647	0.3022	0.7943	0.2789	0.4974	0.1698
South Korea	0.8612	0.3268	0.8550	0.3243	0.3737	0.1394
Malaysia	0.7888	0.1998	0.7955	0.1992	0.2922	0.0684
Singapore	0.8337	0.3577	0.8694	0.3714	0.5820	0.2356
Total Mean	0.8172	0.2907	0.7887	0.2799	0.4295	0.1507
Group 2						
Australia	0.0872	0.0272	0.0818	0.0257	0.0365	0.0116
Indonesia	0.2907	0.0537	0.2753	0.0511	0.0731	0.0127
New Zealand	0.0549	0.0115	0.0532	0.0112	0.0223	0.0045
Philippine	0.3428	0.0671	0.3322	0.0650	0.0972	0.0187
Thailand	0.2542	0.1185	0.2499	0.1169	0.0703	0.0314
Vietnam	0.3403	0.0894	0.3481	0.0902	0.0768	0.0198
Total Mean	0.2283	0.0607	0.2234	0.0594	0.0627	0.0164

Source: Author's calculation.

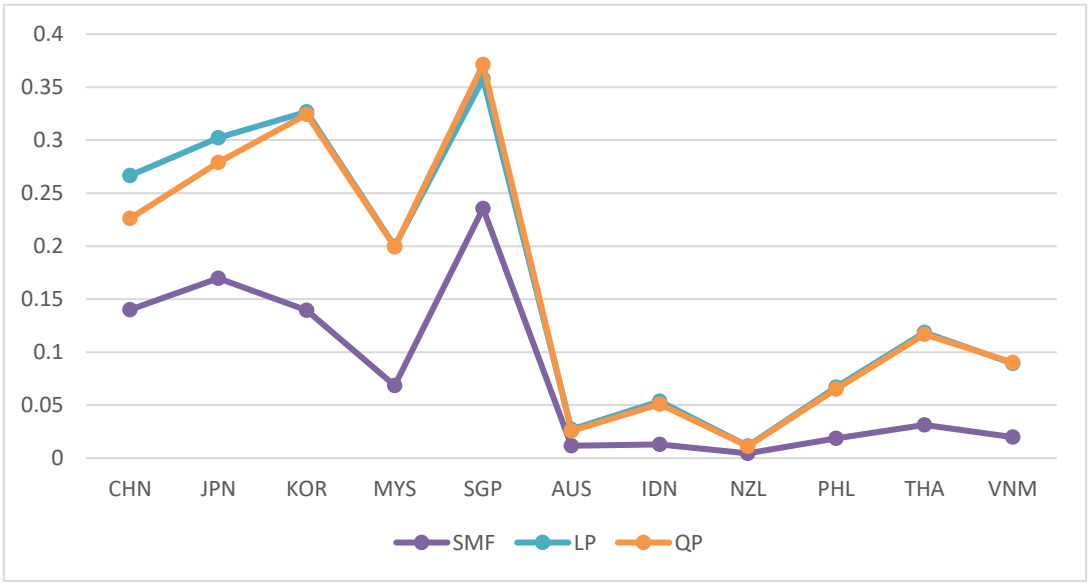
Figures 3.4 and 3.5 provide a more straightforward presentation of the comparisons between LP, QP, and SMF by visualizing the estimates in the table above.

Figure 3.4 Estimations of MTR by SMF, LP, and QP



Source: Author's calculation.

Figure 3.5 Estimations of TEM by SMF, LP, and QP



Source: Author's calculation.

The estimated MTRs from the three estimation methods have the same tendency between groups. The average MTRs of Group 1 are substantially higher than those of Group 2, which indicates that the restricted technology set in Group 1 is more

efficient than the restricted technology set in Group 2. Dominated by this difference, the calculated TEMs based on equation (18) have the same tendency. The highest value of the estimated TEM in the second group is 0.1185, which comes from Thailand's LP estimate. However, the average TEM estimation for the first group by LP is 0.2907. Overall, all countries in Group 1 enjoy a more advanced technology set and have better trade performance than countries in Group 2. This is direct evidence that exports from countries from Group 1 are structurally and substantially more efficient than Group 2.

Although SMF generates a similar tendency to LP and QP, the absolute values of the SMF estimates are significantly different from the LP and QP estimates. The intervals of the MTR estimations for Group 1 are 0.7376 to 0.8647 by LP and 0.6292 to 0.8694 by QP, while this interval in the SMF estimates reduces to 0.2922 to 0.5820. This difference is even more obvious in the estimations for Group 2. The MTRs in the LP and QP results are almost four times those in the SMF results. This finding partially agrees with Huang *et al.* (2014) that the LP and QP estimation results may be biased as they failed to accommodate the effect of the random shock in the metafrontier function. However, in this paper, the average MTRs estimated by SMF are smaller than those by LP and QP, which is contrary to the findings of Huang *et al.* (2014).

This paper also finds that different methodologies generate opposite trends in the estimated MTRs for each country. As shown in Table 3.4, the significantly positive *eta* in the SMF regression demonstrates that each country's MTR is increasing over the sample period. However, the calculations of LP and QP show that each country's MTR is decreasing over time. More comprehensive MTR estimations are listed in Appendix 3.II.

To sum up, no matter by which method, the TEM estimations suggest that huge potential exists for all RCEP countries to improve the performances of their renewable energy commodities exports, and the implicit trade cost significantly

hinders the export value within this region. Countries in the first group achieve higher average scores in both TEG and MTR, and thus higher average scores in TEM than the second group. LP and QP provide relatively higher MTR estimates for both Group 1 and Group 2, with approximate average values of 0.8 and 0.22, respectively. The average MTRs generated by SMF are much lower than the former numbers, which are 0.4295 for Group 1 and 0.0627 for Group 2.

3.6 Conclusion

It is acknowledged that when countries are able to work together, it will have increasingly important implications for national, regional, and worldwide prospects of a more sustainable energy future. Collaboration among countries with respect to developing new and innovative strategies could increase the phase of moving toward low-carbon-intensive energy systems. Such collaborative actions that countries take would have impacts beyond their borders and by nature facilitate a more win-win situation for all countries globally. Although the availability of cost-effective and potentially efficient renewable energy technologies is a necessary condition for the promotion of green growth nationally and internationally, determined commitment to make use of such technologies by nations is thus crucial. International trade in renewable energy commodities provides an effective way of achieving NDCs nationally, even when individual countries may not have sufficient infrastructure readily available to them to fulfill NDCs. The establishment of RCEP provides an excellent opportunity for Asia-Pacific countries to enhance trade within this region. Under this circumstance, it is necessary to examine whether renewable energy goods exports have been flowing without constraints in the Asia-Pacific region.

This paper applied the gravity model with a metafrontier approach to evaluate renewable energy commodities export performances of selected RCEP members. The metafrontier approach decomposed the total trade efficiency score into two components, a trade efficiency score with respect to the group frontier and the

meta-technology ratio of the restricted technology set to the unrestricted technology set. In the first step, the SFA regression result confirmed the assumption that the two groups have different technologies and estimated each country's TEG and the values of the group production frontiers. Based on the estimations in the first step, this paper applied LP, QP, and SMF to measure the MTRs. The results show that Group 1 has a significant higher average MTR than Group 2, which means that countries in Group 1 are more technically efficient in adopting the unrestricted technology set for trade. This is direct evidence that exports from countries from Group 1 are structurally and substantially more efficient than those of Group 2. Differences in MTRs dominated the TEM calculations, which meant that countries' TEMs in Group 1 were overwhelmingly higher than those in Group 2. Overall, countries with relatively higher export values of renewable energy commodities performed better in realising their trade potentials than other countries. However, the small numbers of the TEM show that all RCEP members need to work harder to reduce the implicit trade costs. The establishment of RCEP does have the potential to considerably improve trade in renewable energy commodities within the Asia-Pacific region.

This paper also finds evidence that there exists a significant random error in the metafrontier function, which supports the conclusion from Huang *et al*. (2014). The absence of the random shock in LP and QP would cause biased estimations. Therefore, SMF is preferred in the second step when measuring the metafrontier function. However, in this paper, the SMF estimation generated smaller MTRs than the LP estimation and QP estimation, which is contrary to the result in Huang *et al*. (2014).

This study proposes the following policy suggestions based on the estimation results. For countries in Group 2, their priority is to upgrade their technology set for exporting renewable energy goods, and the best way is to learn from the successful experiences of countries in Group 1. According to O'Donnell *et al.* (2008), the technology gap between group frontiers and the metafrontier is mainly affected by the production

environment, such as infrastructure and endowment availabilities. So, governments from the second group should spend more on improving transportation infrastructure. Secondly, governments should actively engage in promoting R&D activities and protecting intellectual property rights concerning renewable energy production, which are essential for countries to integrate with the world market. Thirdly, countries in Group 2 should seek more regional and international cooperation, including attracting more foreign direct investment and skilled labour, to improve the quality of their renewable energy commodities. Joining the RCEP framework is good practice for this process.

For countries in Group 1, their technology set is already relatively advanced. Therefore, they should focus on how to effectively eliminate implicit trade costs, especially non-tariff measures in importing countries. For example, governments should make use of the terms of Trade in Service and Temporary Movement of Natural Persons in the RCEP agreement effectively to facilitate labour movement and exchange of professional services related to the renewable energy sector. More efficient articles should also be formed in the Intellectual Property section to promote innovation recognition and distribution. The next chapter conducts detailed examination on what factors contribute to the implicit trade cost within the RCEP region and provides policy suggestions for governments on how to minimize trade inefficiency.

3.7 Appendix 3.I

Table 3.6 HS code of renewable energy commodities from the APEC 54 list

HS code	Commodities
840290	Steam or other vapor generating boilers; super-heated water boilers
840490	Parts for auxiliary plant for boilers, condensers for steam, vapor power unit
840690	Parts for steam and other vapor turbines
841182	Gas turbines, except turbojets and turbo-propellers, of a power exceeding 5,000 kW
841199	Parts of gas turbines (841182)
841290	Engine and motor parts, nesoi (wind turbine blades and hubs)
841919	Instantaneous or storage water heaters, nonelectric other than instant water heaters
841990	Parts of machinery, plant or laboratory equipment involving temperature change, nesoi
850164	AC generators (alternator), of an output exceeding 750 kVA
850231	Other electric generating sets: wind-powered
850239	Electric generating sets and rotary convertors: other
850300	Parts suitable for use solely or principally with the machines of heading 8,501 or 8,502
850490	Parts for electrical transformers, static converters, and inductors
854140	Photosensitive semiconductor devices, including photovoltaic cells
901380	Optical devices, appliances, and instruments, nesoi
901390	Parts and accessories for optical devices, appliances, and instruments, nesoi

3.8 Appendix 3.II

Table 3.7 TEG, MTR, and TEM estimates by LP, QP, and SMF

Countries' yearly average TEG, 2006 to 2014

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014
Group 1									
China	0.295885	0.312471	0.32935	0.346472	0.363789	0.381253	0.398814	0.416427	0.434046
Japan	0.278587	0.296124	0.313937	0.331977	0.350189	0.368523	0.386928	0.405354	0.423755
Korea	0.320254	0.335579	0.351178	0.367012	0.383044	0.399232	0.415538	0.431922	0.448344
Malaysia	0.185997	0.201801	0.218136	0.234955	0.252207	0.269839	0.287798	0.306028	0.324476
Singapore	0.355446	0.374257	0.393089	0.411895	0.430626	0.44924	0.467695	0.485951	0.503975
Group 2									
Australia	0.314387	0.318809	0.323244	0.327692	0.332151	0.336621	0.341102	0.345591	0.350089
Indonesia	0.162435	0.166221	0.170047	0.173913	0.177819	0.181763	0.185744	0.189763	0.193818
New Zealand	0.167439	0.171239	0.175078	0.178956	0.182873	0.186827	0.190818	0.194846	0.198908
Philippines	0.170458	0.17418	0.177941	0.181739	0.185574	0.189445	0.193352	0.197293	0.222832
Thailand	0.448141	0.452224	0.456306	0.460388	0.464468	0.468547	0.472624	0.476697	0.480767
Vietnam	0.210338	0.214121	0.217937	0.221787	0.225668	0.229581	0.233525	0.2375	0.233538

Countries' yearly average MTR by LP, 2006 to 2014

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014
Group 1									
China	0.736811	0.737818	0.738632	0.737372	0.736838	0.738523	0.738923	0.737536	0.736086
Japan	0.872879	0.870175	0.86892	0.866496	0.864667	0.86453	0.86345	0.857489	0.853668
Korea	0.870441	0.869245	0.864471	0.859854	0.85944	0.859343	0.858187	0.855804	0.853899
Malaysia	0.794674	0.794052	0.793411	0.788154	0.787816	0.787959	0.786899	0.784253	0.781656
Singapore	0.842644	0.841317	0.837303	0.833255	0.832553	0.832459	0.830866	0.82789	0.824783
Group 2									
Australia	0.071013	0.077531	0.075215	0.080012	0.086381	0.090928	0.094686	0.099758	0.109014
Indonesia	0.251381	0.269271	0.272352	0.265779	0.273602	0.292398	0.312694	0.330246	0.348186
New Zealand	0.046637	0.049565	0.051547	0.050012	0.051698	0.055551	0.059385	0.062179	0.064815
Philippines	0.306215	0.325402	0.331986	0.343145	0.380274	0.413427	0.426065	0.427774	0.391728
Thailand	0.204303	0.218177	0.225848	0.228123	0.247513	0.272938	0.285899	0.293704	0.311207
Vietnam	0.31546	0.336891	0.330045	0.330473	0.37335	0.397386	0.404026	0.403156	0.379041

Countries' yearly average MTR by QP, 2006 to 2014

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014
Group 1									
China	0.633213	0.629978	0.627846	0.631837	0.627958	0.625831	0.626648	0.628349	0.630889
Japan	0.794568	0.792448	0.79075	0.796076	0.79187	0.790253	0.792441	0.797544	0.802343
Korea	0.855176	0.851853	0.852332	0.859795	0.854062	0.851782	0.853766	0.856299	0.859693
Malaysia	0.80117	0.796836	0.794167	0.799977	0.7941	0.791016	0.7918	0.794032	0.796808
Singapore	0.879946	0.873518	0.869012	0.873297	0.867065	0.863369	0.86364	0.865834	0.869104
Group 2									
Australia	0.065924	0.071755	0.069887	0.07552	0.081135	0.085056	0.088675	0.094118	0.103836
Indonesia	0.237338	0.253403	0.256568	0.253124	0.257971	0.274706	0.295084	0.314588	0.335012
New Zealand	0.045407	0.048109	0.049901	0.049029	0.05014	0.053612	0.057573	0.060864	0.064208
Philippines	0.292467	0.309329	0.316645	0.330511	0.364218	0.395318	0.408709	0.413649	0.38375
Thailand	0.198713	0.211527	0.219705	0.224966	0.242843	0.267534	0.281197	0.291024	0.311594
Vietnam	0.319911	0.340675	0.333906	0.33685	0.379448	0.402933	0.410691	0.412867	0.392361

Countries' yearly average MTR by SMF, 2006 to 2014

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014
Group 1									
China	0.373854	0.380857	0.387877	0.394911	0.401955	0.409008	0.416065	0.423125	0.430184
Japan	0.471409	0.477918	0.48442	0.490913	0.497396	0.503866	0.51032	0.516757	0.523174
Korea	0.344866	0.352039	0.359236	0.366454	0.373689	0.380939	0.3882	0.395469	0.402744
Malaysia	0.263798	0.270782	0.277818	0.284901	0.29203	0.2992	0.306409	0.313653	0.320928
Singapore	0.55899	0.564804	0.570598	0.57637	0.582119	0.587842	0.593538	0.599206	0.604843
Group 2									
Australia	0.027169	0.02924	0.031424	0.033725	0.036144	0.038685	0.04135	0.044141	0.047061
Indonesia	0.057873	0.061375	0.065012	0.068785	0.072696	0.076744	0.08093	0.085253	0.089713
New Zealand	0.015737	0.017139	0.018633	0.020225	0.021918	0.023714	0.025618	0.027633	0.029761
Philippines	0.0868	0.091182	0.095695	0.10034	0.105114	0.110018	0.115051	0.12021	0.113314
Thailand	0.055483	0.058872	0.062395	0.066052	0.069846	0.073776	0.077843	0.082046	0.086387
Vietnam	0.065287	0.069052	0.072952	0.076989	0.081162	0.085473	0.089919	0.094502	0.093777

Countries' yearly average TEM by LP, 2006 to 2014

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014
Group 1									
China	0.216099	0.228605	0.241328	0.253526	0.266231	0.279707	0.292729	0.304976	0.317366
Japan	0.242602	0.256977	0.272104	0.28697	0.302222	0.317943	0.333431	0.346817	0.360993
Korea	0.275673	0.28848	0.30035	0.312293	0.32615	0.339952	0.35324	0.365982	0.379166
Malaysia	0.147659	0.160137	0.173035	0.185207	0.198799	0.212689	0.226572	0.240141	0.253824
Singapore	0.299067	0.31437	0.328563	0.342585	0.357809	0.373206	0.387803	0.401477	0.414827
Group 2									
Australia	0.02041	0.022809	0.022509	0.024297	0.026807	0.02873	0.030381	0.03274	0.036269
Indonesia	0.041887	0.045976	0.047655	0.047795	0.050366	0.055096	0.060155	0.064991	0.069724
New Zealand	0.008951	0.009796	0.010344	0.010198	0.010808	0.011881	0.012943	0.013919	0.014814
Philippines	0.052322	0.05627	0.05903	0.062535	0.070332	0.077849	0.081795	0.083125	0.086578
Thailand	0.090956	0.097846	0.102861	0.105771	0.115785	0.12871	0.135641	0.139867	0.149088
Vietnam	0.08073	0.086107	0.086243	0.088805	0.100556	0.108135	0.111294	0.110216	0.101572

Countries' yearly average TEM by QP, 2006 to 2014

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014
Group 1									
China	0.184495	0.193941	0.203741	0.216017	0.225452	0.235547	0.246873	0.258609	0.270805
Japan	0.221516	0.234803	0.24847	0.264606	0.277611	0.291592	0.307038	0.323724	0.340468
Korea	0.270824	0.282622	0.295762	0.311934	0.32336	0.336128	0.350783	0.365749	0.381197
Malaysia	0.14623	0.158119	0.170733	0.185483	0.197891	0.211143	0.225676	0.240967	0.256599
Singapore	0.309681	0.323992	0.338885	0.35721	0.370879	0.385447	0.401615	0.418609	0.436006
Group 2									
Australia	0.01909	0.02125	0.021047	0.023077	0.025316	0.027005	0.028586	0.031005	0.03467
Indonesia	0.039761	0.043482	0.045083	0.045693	0.047649	0.051921	0.056942	0.062075	0.067284
New Zealand	0.008737	0.009522	0.010027	0.010011	0.010492	0.011473	0.012553	0.013621	0.014667
Philippines	0.05005	0.05363	0.056392	0.060318	0.067496	0.074615	0.078651	0.08063	0.084706
Thailand	0.088882	0.095317	0.100416	0.104562	0.113847	0.126436	0.133753	0.139008	0.149748
Vietnam	0.080664	0.085921	0.086045	0.089204	0.100845	0.108283	0.11179	0.111759	0.104072

Countries' yearly average TEM by SMF, 2006 to 2014[4]

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014
Group 1									
China	0.10338	0.111742	0.120473	0.129562	0.138992	0.148746	0.158807	0.169155	0.179769
Japan	0.125531	0.135793	0.146433	0.157427	0.168751	0.18038	0.192286	0.204442	0.216822
Korea	0.105223	0.113037	0.121184	0.129656	0.138442	0.147529	0.156905	0.166553	0.176459
Malaysia	0.043478	0.048798	0.054514	0.060628	0.067138	0.074041	0.081331	0.088998	0.097034
Singapore	0.182384	0.195172	0.208233	0.221533	0.235038	0.248715	0.262532	0.276456	0.290458
Group 2									
Australia	0.00808	0.008831	0.009636	0.010498	0.01142	0.012404	0.013452	0.014568	0.015753
Indonesia	0.009126	0.009909	0.010745	0.011634	0.012579	0.013582	0.014645	0.01577	0.01696
New Zealand	0.002925	0.003246	0.003594	0.003973	0.004385	0.004831	0.005313	0.005833	0.006394
Philippines	0.014457	0.015541	0.016685	0.017891	0.019162	0.020498	0.021901	0.023374	0.024898
Thailand	0.023674	0.025385	0.027185	0.029075	0.031059	0.033138	0.035314	0.037588	0.039963
Vietnam	0.016276	0.017447	0.018679	0.019975	0.021336	0.022765	0.024262	0.025829	0.025363

Source: Author's calculation.

[4] Even though LP (linear optimization) and QP (quadratic optimization) are similar, different observations were given different weights in calculation. SMF uses the stochastic frontier method including a random error term. Theoretically, they should generate different results.

Chapter 4 Identifying Triggers and Barriers for Trade in Renewable Energy Commodities in RCEP Countries: Evidence Based on China's Export Data

Summary

This paper uses an augmented gravity equation with a one-step SFA method to analyse China's export frontier and export efficiency of renewable energy commodities to other RCEP members. It finds that policy instruments related to the renewable energy sector in the exporting country have a significant positive impact on improving export efficiency. Moreover, the size of the renewable energy market in the exporting country has a mixed effect on renewable energy commodities exports. A larger renewable energy market would increase the export frontier, but also reduce the export efficiency score. Finally, the estimation reveals that the innovation process in China becomes one of the implicit trade costs in its renewable energy commodities export, which highlights the need to establish more commonly accepted technical regulations and technology transfer systems between RCEP countries.

4.1 Introduction

Increasingly, growing environmental issues, such as climate change and greenhouse gas emissions, have become major concerns for all countries in the world. The 2030 Agenda for Sustainable Development clearly states that climate change is currently one of the greatest challenges, and Sustainable Development Goal (SDG) 13 requires member states to take 'urgent action' to mitigate climate change and its impacts. Meanwhile, how to secure energy supply has also become a key factor for maintaining sustainable development. Under such macro circumstances, policy makers and investors in both public and private sectors have concentrated on developing renewable energy technology to deal with the above problems.

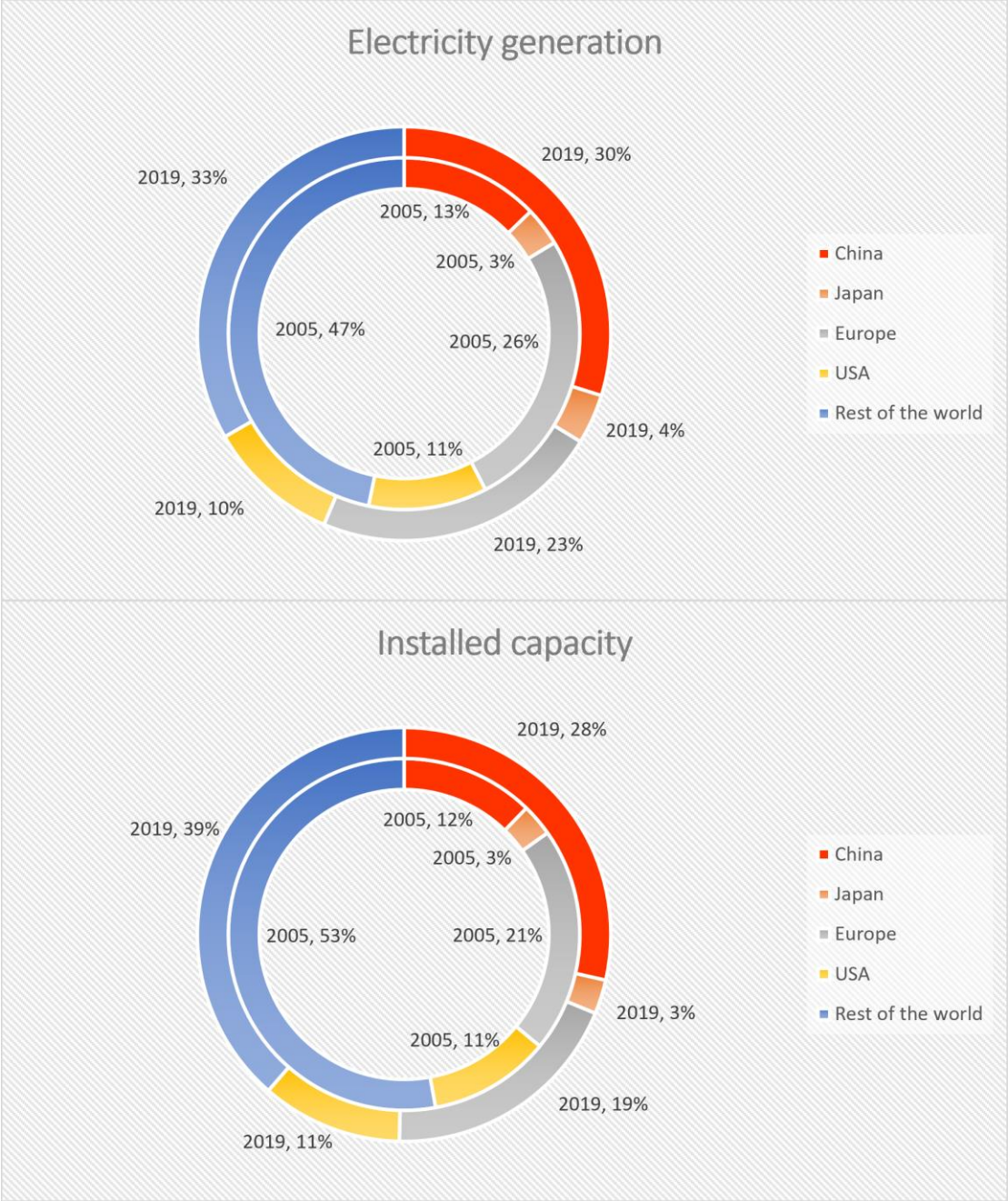
Indeed, renewable energy in the electricity generation sector has experienced significant growth in generation capacity and, more importantly, cost reductions, over the past decade. According to the International Renewable Energy Agency (IRENA), the world average levelised cost of electricity (LCOE) dropped dramatically, from 0.381 U.S. dollars per kilowatt-hour (USD/kWh) to 0.061 USD/kWh for solar photovoltaic (PV) power, from 2010 to 2019, and from 0.089 USD/kWh to 0.045 USD/kWh for onshore wind power. These prices are already very competitive against fossil fuels in the electricity generation market (Renewable Energy Policy Network for 21st Century (REN21) 2020). Regional cooperation and trade in renewable energy commodities can play an important role in sustaining the price competitiveness of the renewable energy systems in the electricity generation market and providing access to more advanced renewable energy technologies (Zhao *et al.* 2016). Moreover, Chapter 2 demonstrates that trade in renewable energy goods can improve the efficiency of funds used in adding more renewable energy power plants.

Trade liberalisation in renewable energy goods matters even more for countries in the Asia-Pacific region, as they have strong incentives to speed up the development of the renewable energy sector. Alongside the considerable economic accomplishments in

RCEP countries, rapidly increasing energy demand causes dilemmas about how to balance energy security and environmental pollution, while renewable energy provides a straightforward solution to it. In addition, by expanding renewable energy industries to close the energy gap in this area, countries can create great opportunities to transfer to a sustainable economic development path (Liu and Goldstein 2013). Chapter 3 proves that there is huge potential for the growth of renewable energy goods export within RCEP members, and that the implicit trade cost, namely the trade inefficiency term caused by non-tariff trade barriers, significantly and negatively impacts the trade value. However, which factors contribute to the implicit trade cost in renewable energy exports and how to reduce the implicit trade cost remain unanswered in the literature.

Based on the data on China's exports to other RCEP members, this paper empirically analyses the determinants of the implicit trade cost in renewable energy commodities trade within the RCEP region. China has achieved great success in the development of renewable energy technology. According to IRENA, the combined newly installed electricity generation capacity of solar PV and onshore wind in China was 53,134 megawatts (MW) in 2019, increased from 12,543 MW in 2010. The cumulative capacity of solar PV and onshore wind reached 204,575 MW and 203,652 MW in 2019, respectively. As comparisons, the corresponding cumulative capacities are 59,068 MW and 103,641 MW in the U.S., and 140,226 MW and 174,285 MW in all European countries, respectively. Moreover, electricity generation by renewable energy sources was 2,014,902 gigawatt hours (GWh) in 2019, accounting for almost 27 per cent of China's total electricity generation (International Energy Agency (IEA) data and statistics). Figure 4.1 shows China's considerable achievement of developing its renewable energy sector.

Figure 4.1 Renewable energy electricity generation and installed capacity, 2005 and 2019, in proportion

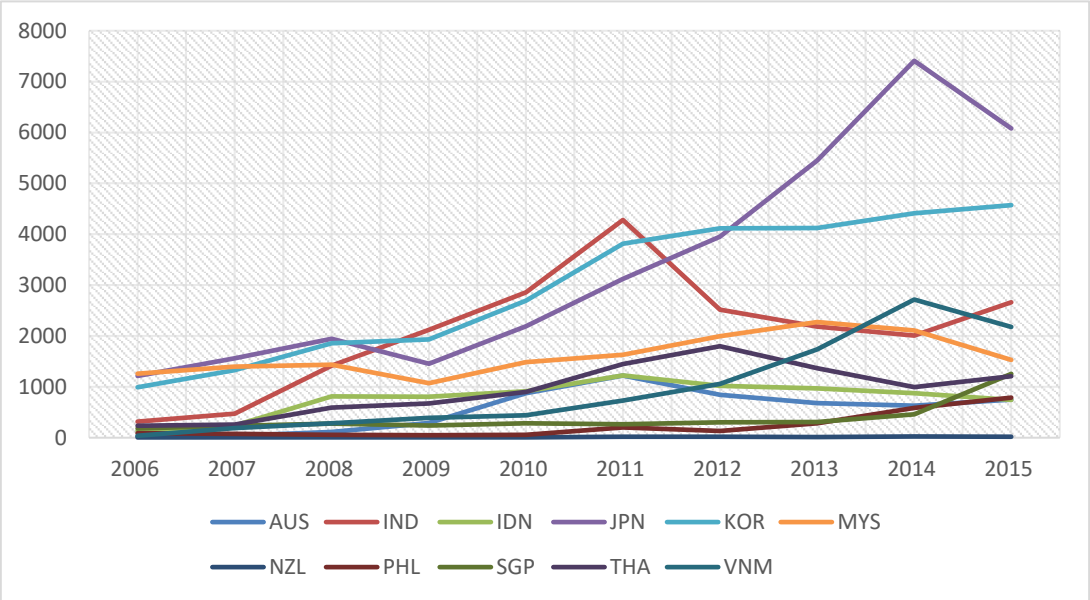


Source: IRENA statistics.

In addition, China invested 97.6 billion dollars in the renewable energy power generation sector in 2019, which consolidated its leadership in the world renewable energy investment market (Bloomberg New Energy Finance (BNEF)). Meanwhile,

China is a decisive player in the international market for exporting renewable energy commodities, as it owns five of the six largest solar module manufacturers and the largest wind turbine producer in the world (Chiu 2017). Figure 4.2 shows China's exports of renewable energy-related goods to its trading partners in the Asia-Pacific region. Although the export values fluctuate in some countries, such as India and Singapore, China's exports of renewable energy goods experienced a significant increase to all partners except Malaysia.

Figure 4.2 Exports of renewable energy commodities from China, 2006 to 2015, million US dollars



Source: UN comtrade.

It is well acknowledged that China has already become the world leader in renewable energy development and trade. Identifying the triggers and barriers of China's renewable energy commodities exports to RCEP countries is meaningful for the following reasons. First, China's successful experiences provide hints for other RCEP members on how to improve their export performance and reduce implicit trade barriers within this region. Second, China is one of the few locations where building solar PV and wind energy plants is already cheaper than operating existing coal-fired

power plants (REN21 2020). Understanding and improving the trade performance of China's exports can effectively reduce the construction cost for other RCEP countries.

This paper adopts the gravity model with a one-step stochastic frontier analysis (SFA) method to analyse the determinants of China's renewable energy commodities exports to other RCEP countries. Particularly, the SFA method enables this paper to recognise which factors impact trade inefficiency terms in exports and then to figure out how to improve trade performance. This paper finds that although China is achieving remarkable success in exporting renewable energy commodities, trade inefficiency is still significant. Second, the prices of renewable energy goods play important roles in determining trade flows. Third, the renewable energy market size and renewable energy innovations in the domestic country can certainly improve renewable energy exports, however, they also increase the technical inefficiency in trade.

The rest of this paper is structured as follows. Section 2 reviews the existing literature. Section 3 elaborates the differences between the one-step and two-step SFA methods. Section 4 discusses the variables used in the empirical regression and presents the complete model. Section 5 shows the results of empirical works, and Section 6 gives conclusions.

4.2 Literature review

Only a handful of papers have evaluated the performance of China's renewable energy commodities exports. Liu and Goldstein (2013) review the development patterns of solar PV and wind energy technologies in China, and they suggest that the support of renewable energy policies noticeably contributes to the rapid growth of China's renewable energy supply in both the domestic and international markets. Groba and Cao (2014) apply an augmented gravity model to inspect the driving forces of China's solar PV and wind energy commodities exports to 43 major trade partners. They find that the renewable energy market size, renewable technology innovations,

and renewable energy policies in importing countries have positive effects on the renewable energy commodities exports. Zhao *et al.* (2016) also use the gravity model with a larger data set, which includes 116 importing countries, while they focus on testing the effects of tariff reduction on China's exports. In particular, they indicate that tariff reduction not only improves existing export volumes, but also induces exports to new energy markets.

A few other studies examine the determinants of renewable energy commodities trade in other countries or regions. When analysing the driving forces of world renewable energy trade, Jha (2009) finds that the effect of reducing tariff rates may not be as significant as other factors, and that tariff reduction itself cannot effectively improve the export of renewable energy goods. Algieri *et al.* (2011) analyse the trade flows of major solar PV exporters at the world level and find a long-run relationship between export values and relative prices of solar PV goods based on U.S. export data. Conversely, Sawhney and Kahn (2012) classify the determinants of renewable energy goods export to the U.S. Their findings imply that the outflow of foreign direct investment from the U.S. can improve its imports of high-tech renewable energy equipment from receiving countries. In addition, the findings also illustrate that renewable energy electricity generation in exporting countries has a positive impact on exports to the U.S. By using export data across East Asia Summit countries, Moinuddin and Bhattacharya (2013) show that tariff reduction can effectively boost the export within the region. Kuik *et al.* (2019) argue that renewable energy policies in exporting countries are positively correlated with the competitive advantages of those countries' solar PV and wind energy products, while they use installed capacity to represent the stringency of renewable energy policies.

A strand of papers particularly emphasises investigating the effect of environmental regulations on the export in renewable energy goods. Constantini and Crespi (2008) inspect the impacts of environmental regulations, which are proxied by CO_2 emissions,

on both exporters and importers on renewable energy technology exports from developed countries to the world. They find that environmental regulations in exporting countries can significantly facilitate export values, but regulations in importing countries have no effect. In addition, the technological capabilities show the same consequences that innovations and R&D investments in exporting countries have positive effects on export performance, while their counterparts in importing countries do not. Constantini and Mazzanti (2012) find similar results for the renewable energy exports of the European Union, while they use energy and environmental taxation to represent the environmental regulations. Constantini and Crespi (2013) further illustrate that different types of environmental policies have different effects on exports, using export data from 20 OECD countries. In contrast, Cantore and Cheng (2018) focus on examining the effects of environmental regulations in importing countries on environmental goods exports based on 71 countries' environmental goods export data. They provide evidence that environmental regulatory stringency, represented by environmental taxes, in exporting countries has a significantly negative impact on trade flows.

The most relevant research is the work of Kalirajan *et al.* (2019) which finds significant trade inefficiencies in China's renewable energy commodities exports by applying the SFA method. However, their paper does not consider the effects of factors from the renewable energy market on export values. Moreover, they do not identify which factors can influence the estimated trade inefficiency.

To the author's best knowledge, no research has previously been conducted to estimate which factors contribute to the implicit trade cost of China's renewable energy commodities exports. This paper fills this research gap.

4.3 Theoretical framework

SFA has been widely used in estimating technical efficiency in varied economic areas.

Many studies, including Chapter 2, apply a two-step SFA approach to analyse what factors contribute to the technology inefficiency term. In the first step, a standard stochastic production function is estimated, expressed as:

$$\ln Y_{it} = \ln f(X_{it}, \beta) - u_{it} + v_{it} \quad (1)$$

$$u_{it} \sim N^{+}(u, \sigma_u^2), v_{it} \sim N(0, \sigma_v^2) \quad (2)$$

The second step usually performs a linear regression on the inefficiency term based on the estimated values of u_{it} from the first step, expressed as:

$$u_{it} = f'(Z_{it}, \delta) \quad (3)$$

where Z_{it} is a vector of variables which can either be exogenous or come from X_{it}, and $f'(.)$ is commonly assumed to be a linear expression. The estimates of the above equation show how the variables Z_{it} affect technical inefficiency. More information about how the two-step SFA is derived can be found in Chapter 2.

According to equation (3), u_{it} is treated as an expected variable in the second step. As an alternative to the two-step method, a one-step method is proposed in the literature, which includes Z_{it} when estimating the production frontier and inefficiency levels. The term 'one-step' means that all coefficients in equations (1) and (3) are estimated simultaneously, not sequentially in two steps.

The one-step SFA method has several calculation approaches. The main idea of all methods is to allow the parameters of u_{it}'s presumed distribution to depend on Z_{it}. Kumbhakar *et al.* (1991), Huang and Liu (1994), and Battese and Coelli (1995) propose the most commonly used approach, which replaces the constant mean of the inefficiency distribution in equation (2) but keeps the variance as a constant, expressed as:

$$u_{it} \sim N^{+}(f'(Z_{it}, \delta), \sigma_u^2) \quad (4)$$

where $f'(Z_{it}, \delta)$ is the same as equation (3), and Z_{it} includes a constant term.

An alternative method is to scale the variance of u_{it}'s distribution. Reifschneider and Stevenson (1991), Caudill and Ford (1993), and Caudill *et al.* (1995) propose the method that assumes the variance of u_{it}'s distribution is determined by an exponential equation of Z_{it} while the mean of u_{it} remains unchanged, expressed as:

$$u_{it} \sim N^{+}\left(u, \sigma_{u_{it}}^{2}\right) \tag{5}$$

$$where\ \sigma_{u_{it}} = \exp(Z_{it}, \delta)\, \sigma_{u} \tag{6}$$

Wang and Schmidt (2002) suggest another approach that scales both the mean and variance parameters. They replace the original inefficiency term in equation (1) by a new term u_{it}^{*}, which multiplies u_{it} by a monotonic function $g(.)$. u_{it}^{*}'s calculation and distribution are formulated as:

$$u_{it}^{*} = g(Z_{it}, \delta) u_{it}, and\ g(Z_{it}, \delta) \geq 0 \tag{7}$$

$$u_{it}^{*} \sim N^{+}(u g(Z_{it}, \delta), \sigma_{u}^{2} g(Z_{it}, \delta)^{2}) \tag{8}$$

The vector Z_{it} in equations (6), (7), and (8) is slightly different from the one in equation (4). The former Z_{it} fully consists of exogenous variables other than input variables in the stochastic production function, and it does not include a constant term (Belotti *et al.* 2013).

This study (Chapter 4) adopts the first one-step calculation approach identified by equation (4), instead of methods identified by equation (5) and equation (8), for the following reasons. Compared with other calculations methods, the first calculation method allows interactions between X_{it} and Z_{it}, which is true for the model used in this study. Moreover, this paper is interested in which factors can increase (or decrease) the magnitude of the trade efficiency of China's renewable energy commodities export, not the technical inefficiency term's variations. Therefore, it is

more appropriate to scale the mean of the inefficiency term, instead of scaling the deviation.

4.4 Model specification and data description

This paper adopts the gravity model with the one-step SFA method to measure the determinants of China's export performance. The panel data set consists of China's renewable energy commodities exports to other 10 RCEP members, namely Australia, Indonesia, Japan, Republic of Korea, Malaysia, New Zealand, Philippines, Singapore, Thailand, and Vietnam, from 2006 to 2015. The basic form of the regression equation is formulated as:

$$\ln REX_{it} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln Pop_{it} + \beta_3 \ln Dist_{it} + \beta_4 \ln Taf_{it} \quad (9)$$

$$+\beta_5 \ln Ex_{it} + \theta' C_{it} - u_{it} + v_{it}$$

$$where\ u_{it} = \delta_0 + \delta' Z_{it} \quad (10)$$

In equation (9), the dependent variable REX_{it} represents the value of renewable energy exported from China to importing country *i* at time *t*. *GDP* and *Pop* are the importer's total income and population. The typical explicit trade costs are proxied by *Dist* and *Taf*, which are the geographical distance between China and its trade partners and tariff rates in importing countries, respectively. *Ex* is the relative exchange rate, of which a higher value means that the exporter's currency appreciates relative to the importer's currency. The above explanatory variables are commonly proposed by the conventional gravity model. C_{it} is a vector of other control variables which can directly affect China's export frontier and are specified for the renewable energy sector. u_{it} is the technical inefficiency term which capture the total effect of implicit trade cost. Z_{it} is a vector of environmental variables which influence the trade inefficiency u_{it}. v_{it} is the random error term, and β, θ, and δ are vectors of coefficients to be estimated.

The positive effect of renewable energy market size in exporting countries has been proved by previous studies (Sawhney & Kahn 2012; Kuik *et al.* 2019; *etc*.). Clearly, a larger renewable energy market in and exporting country indicates stronger supply capacity of renewable energy equipment, and thus a higher export value. This paper uses renewable energy electricity generation as one of the control variables in C_{it} to measure the effect of increased supply capacity, expected to have a positive parameter. However, a larger renewable energy market also suggests higher demand for renewable energy commodities within the exporting country, which may reduce the export value if growth in domestic demand is more than the growth in supply. This effect is considered an indirect impact on trade inefficiency instead of directly on the export frontier, as the potential export reduction is caused by more intensive market competition, which reduces the export efficiency score. To measure the possible negative effect of China's renewable energy market on trade efficiency, this paper introduces the ratio of renewable energy supply to total primary energy supply as an environmental variable that affects u_{it}. This ratio represents the relative expansion rate of the renewable energy sector, and a higher value implies a bigger possibility that growth in demand for renewable energy commodities is faster than growth in supply. Therefore, it is expected to have a positive sign. Besides, Groba and Cao (2014) argue that the renewable energy market size in importing countries also influences renewable energy commodities imports. Renewable energy power generation in importing countries is also added into equation (9) as a control variable, predicted to have a positive sign.

Tariff reduction can effectively facilitate trade flows as it reduces the prices of imported commodities, and most of the existing literature confirms the significant effect of trade liberalisation on renewable energy exports. Similarly, any other factors that can directly change the prices of renewable energy commodities at any point in the exporting process should also have an impact on the export value. The export tax rebate (ETR) satisfies the above description. The ETR system was first introduced by

the Chinese government in 1985, and now many other countries treat it as a very important policy tool to promote exports. It is allowed by the WTO as long as the rebate rate is not larger than the domestic value-added tax rate. The basic idea of ETR is to refund export commodities' value-added tax and consumption tax, which are paid during the production process, to avoid the double taxation problem in international trade. Therefore, a positive ETR rate can reduce the prices of exported commodities and facilitate the trade volume. The ETR imposed on China's renewable energy commodities is considered an effective control variable with a positive parameter.

The effect of technology improvements on renewable energy trade has been widely investigated in the literature. Most previous studies use patent data to proxy innovations, instead of R&D investment. It is argued that R&D investment is only one of the many inputs in the innovative process, while patent data represents the final innovation output, which might be more accurate than R&D data (Cantore & Cheng 2018). However, the estimation result in Chapter 2 shows that the R&D investment is not only used in technology improvement, but directly contributes to the establishment of renewable energy power generation capacity. This finding implies that R&D investment data may have a direct impact on renewable energy commodities exports. Therefore, this paper accommodates both R&D investment and accumulative patent data in renewable energy technology in equations (9) and (10). As the R&D investment in China is an important input in enlarging the renewable energy supply, it is treated as a control variable in C_{it} with an expected positive coefficient. In addition, the number of patents can indicate the technological level and quality of exporting commodities. In other words, with more patents owned by China, its renewable energy products enjoy more comparative advantages in the international market. So, China's patent data is treated as an environmental variable in Z_{it} and predicted to have negative effects on the trade inefficiency term.

There are two opposing theories in the literature about the effect of environmental regulations on export performance. The pollution haven hypothesis argues that the introduction of more environmental regulations would increase production costs, which leads to reductions in exports. On the contrary, Porter and van der Linde (1995) consider that more stringent environmental regulations could induce more innovation activities, which would enhance the competitiveness of export commodities in the international market. Recent empirical studies on the export of renewable energy products find evidence in favour of the latter statement (Constantini & Crespi 2008; Constantini & Mazzanti 2012; Constantini & Crespi 2013). Moreover, it is well acknowledged that supportive policy instruments for renewable energy technologies in exporting countries can effectively improve the production of renewable energy commodities in both domestic and international markets (Liu & Goldstein 2013; Groba & Cao 2014; Kuik *et al.* 2019). This paper also agrees that renewable energy policies have a positive effect on renewable energy commodities exports, while it considers that renewable energy policies work though improving technical efficiency in the exporting process. Therefore, the variable of renewable energy policies is an environment variable in equation (10).

Other implicit trade costs should also be taken into consideration, especially non-tariff measurements in importing countries, which have become the main barriers blocking trade flows by reducing trade efficiency. This paper introduces the trade openness index, which is the ratio of the total import value to GDP in importing countries, to proxy the effect of non-tariff measurements. The higher trade openness, the fewer non-tariff measurements. So, it is predicted to be negatively correlated with the technical inefficiency term u_{it}.

To sum up, the model used in regression is formulated as:

$$\ln REX_{it} = \beta_0 + \beta_1 \ln GDP_{it} + \beta_2 \ln Pop_{it} + \beta_3 \ln Dist_{it} + \beta_4 \ln Taf_{it} \quad (11)$$

$$+\beta_5 \ln Ex_{it} + \beta_6 \ln ETR_t + \beta_7 \ln CRD_t + \beta_8 \ln RES_{it} + \beta_9 \ln CRES_t - u_{it} + v_{it}$$

$$where\ u_{it} = \delta_0 + \delta_1 CREP_t + \delta_2 CPAT_t + \delta_3 Open_{it} + \delta_4 CSEM_t \quad (12)$$

The dependent variable *REX* is the value of China's renewable energy commodities exports. Appendix 4.I lists the categories of renewable energy commodities based on the 6-digital HS code, and the export data is collected from UN Comtrade. Data of *GDP*, *Pop*, and *Ex* come from the World Development Indicators. *Dist* is the distance between the importer's capital city and Beijing, collected from CPEII. *Taf* is collected from the Tariff Download Facility, and a simple average rate of each renewable energy commodity's tariff rate is used in the regression. *ETR* used in regression is the real export tax rebate rate, which is the ratio of the export tax refund to total export values, taken from CPEII. *CRD* represents the China's R&D investment in the renewable energy sector, collected from BNEF. *RES* and *CRES* are the renewable energy electricity generation in importing countries and China, respectively, and *CSEM* is the ratio of renewable energy supply to the total primary energy supply of China. Their data is generated from IEA data and statistics. *CREP* is the number of China's renewable energy policies and regulations in force in each year, taken from the IEA policies database. *CPAT* is the number of cumulative patents in renewable energy technologies innovated in China. This data is generated from IRENA. The data on total import values used in calculating *Open* comes from World Integrated Trade Solution. The following table (Table 4.1) shows the statistical summary of the data set. Two things can be noticed. First, the variable $\ln Taf_{it}$ is calculated as $\ln Taf_{it} = \ln(Taf_{it} + 1)$ to avoid the $\ln(0)$ problem. Second, to ensure that the software can produce estimation results, the units of *CREP*, *CPAT*, and *CSEM* are transferred to hundred, one hundred thousand, and per mil in regression, respectively.

Table 4.1 Data set statistical summary

Variable	Unit	Mean	Std. Dev.	Min	Max
REX	$	2142229237	2210059909	24016851	11447973864
GDP	$million	967092.1567	1476385.111	66371.6648	6203213.121
Pop	unit	73183742.61	68867726.64	4184600	258383257
Dist	kilometre	4559.6820	3005.64845	955.6511	11041.03
Taf	per cent	2.6113	1.9479	0	6.1563
Ex	ratio	455.7957	934.8244	0.1500	3442.3744
ETR	per cent	7.3245	0.9518	5.9009	9.0080
CRD	$billion	1.44	0.385227206	0.8	2
RES	GWh	27881.1593	30817.2629	477	146098.27
CRES	GWh	857569.9	308793.2254	446882	1392598
CREP	unit	74.1	34.0248	34	142
CPAT	unit	78125	49144.5975	15322	161163
Open	ratio	0.4705	0.3641	0.1055	1.6684
CSEM	per cent	0.1881	0.0265	0.1526	0.2385

Source: Author's calculation.

4.5 Results and discussion

This paper uses Stata to operate the one-step SFA regression for equations (11) and (12). Again, the one-step SFA method simultaneously estimates the parameters of both the control variables that affect the stochastic production frontier and the environmental variables that affect the technical inefficiency. The estimation result of one-step SFA is presented in Table 4.2 column (1).

Table 4.2 Estimates of the determinants on China's renewable energy commodities exports to RCEP countries

Dependent variable: ln *REX*

Variables	One-step SFA (1)	Robustness (2)	Robustness (3)
ln *GDP*	1.1475***	1.1407***	1.1462***
	(0.0454)	(0.0447)	(0.0457)
ln *Pop*	0.3463***	0.3392***	0.3471***
	(0.0448)	(0.0450)	(0.0451)
ln *Dist*	-0.1037	-0.1053	-0.1054
	(0.0674)	(0.0673)	(0.0678)
ln *Taf*	-1.2289***	-1.9988***	-1.1296**
	(0.4498)	(0.5919)	(0.4612)
ln *Ex*	-0.0056	-0.0044	-0.0061
	(0.0200)	(0.0198)	(0.0202)
ln *ETR*	0.2152**	0.3028**	0.2459*
	(0.1032)	(0.1370)	(0.1442)
ln *CRD*	0.2356***	0.2196***	0.2377***
	(0.0737)	(0.0695)	(0.0752)
ln *RES*	0.0298		0.0312
	(0.0342)		(0.0350)
ln *CAP*		0.0319	
		(0.0317)	
ln *CRES*	0.9533***		0.8641**
	(0.3637)		(0.3769)
ln *CCAP*		1.5022***	
		(0.4588)	
Cons	-2.4814	11.2081***	-2.0384
	(2.1957)	(1.5717)	(2.2475)
lambda	2.5338***	2.9076***	2.5219***
	(0.0497)	(0.0439)	(0.0510)

(To be continued)

(Continuing)

Variables	One-step SFA (1)	Robustness (2)	Robustness (3)
CREP	-2.1368***	-2.1878***	-2.2895**
	(0.7396)	(0.7329)	(0.9245)
CPAT	1.3325**	1.4618**	
	(0.5773)	(0.5783)	
NCPAT			0.5767**
			(0.2883)
Open	-4.4941***	-4.4845***	-4.4872***
	(0.2380)	(0.2358)	(0.2387)
CSEM	3.4671***	4.0556***	2.9524***
	(0.8195)	(0.8614)	(0.7103)
Cons	1.2439*	0.6353	1.8105***
	(0.7166)	(0.7898)	(0.6170)

Note: ***, **, and * represent significance at a 1 per cent level, 5 per cent level, and 10 per cent confidence level, respectively. Figures in brackets are standard errors of estimates.

Source: Author's calculation.

First, it is necessary to test whether there exists the technical inefficiency term in China's exports. Instead of the *gamma* in two-step SFA, the one-step SFA method uses the estimate of the coefficient *lambda* to examine the presence of u_{it}, which is called the signal-to-noise ratio and calculated as $\lambda = \frac{\sigma_u}{\sigma_v}$. As shown in Table 4.2, the significant value of λ confirms the presence of the technical inefficiency term in the exporting process and implies that u_{it} causes most of the total deviation between the potential and actual export values. Based on the estimation, on average, China's export only realizes approximately 30 per cent of its potential. Therefore, it is appropriate to use SFA to measure the performance of China's renewable energy commodities exports.

The estimated coefficients of the explanatory variables shown in column (1) are almost in line with expectations. The total income and population in importing countries have positive effects on exports, while tariffs imposed by importing

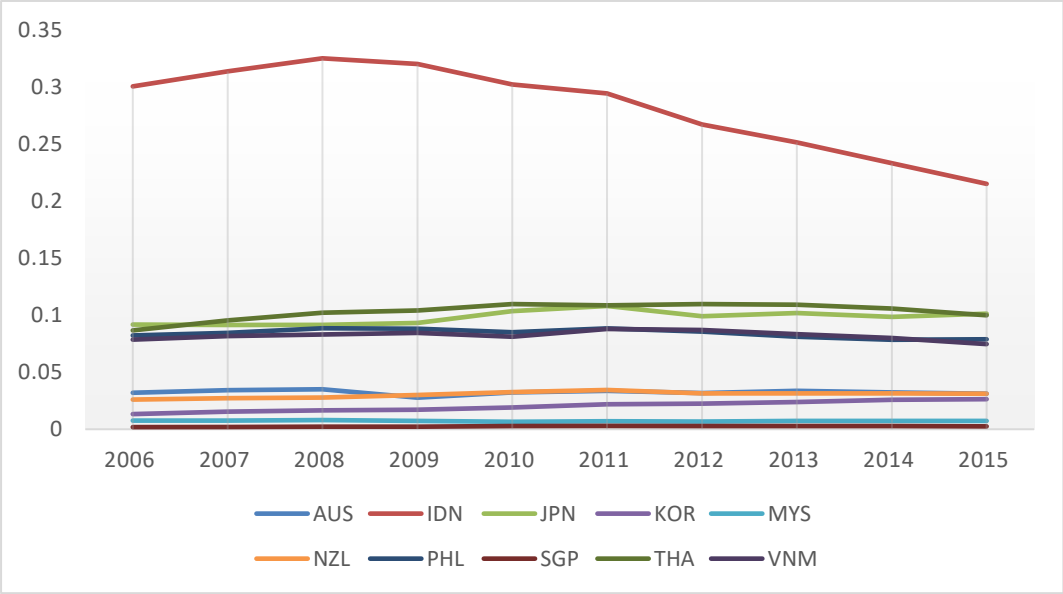
countries have a significant negative impact. *Dist* and *Ex* are negatively correlated with the export values, but the effects are not significant.

This paper is more interested in the estimates of the remaining control variables. First, the export tax rebate imposed by China has a positive effect on its exports to other RECP countries, as expected, which is significant at a 5 per cent confidence level. Although it is not as significant as the estimation of *Taf*, the estimate of *ETR* indicates that reducing export prices can effectively facilitate exports of renewable energy goods. Second, *CRD* has a significant and positive estimated parameter. This finding strongly demonstrates that either public or private sectors should keep focusing on R&D investment in the renewable energy electricity generation sector. *CRES* is also positively correlated with China's export values and is significant at a 1 per cent level. This argument reaffirms the finding in previous literature that a larger renewable energy market size in exporting countries would induce more exports.

RES has a positive coefficient but is not significant. This estimation suggests that the renewable energy market size in other RCEP countries has a very limited effect on their importing from China. This finding implies that the development of other countries' renewable energy power generation sectors will not largely induce more demand for China's commodities exports, but also definitely will not harm the current trade relationship. This paper also uses data on newly installed renewable energy power generation capacity in importing countries and China, represented by *CAP* and *CCAP* respectively, to replace the *RES* and *CRES* variables as proxies for market size to serve as a robustness check. The estimation result is presented in Table 4.2 column (2), and it shows no significant difference from the result in Table 4.2 column (1). This paper attributes this finding to two reasons. First, compared to the demand of renewable energy from China's market, the demand from importing countries is relatively not strong enough to have a significant impact. Figure 4.1 shows the proportion of other countries' total renewable energy supply to China. It clearly shows

that most of the numbers are smaller than 10 per cent, except for Indonesia. However, Indonesia also shows a downward trend after peaking in 2008. Second, as the result demonstrates the existence of significant and high non-tariff barriers which are the main factors impeding trade, the limited demand for renewable energy goods in importing countries cannot affect the already restricted export from China.

Figure 4.3 Ratios of renewable energy supply in importing countries to China, 2006 to 2015



Source: IEA data & statistics

As the result confirms the significant effect of the trade inefficiency, namely the implicit trade cost, how the environmental variables influence the inefficiency term u_{it} becomes the focus of this study. Not surprisingly, *Open* has a significantly negative relationship with u_{it}, which implies that non-tariff measures in RCEP countries considerably reduce the actual trade values of renewable energy commodities from their trade potential. Second, *CREP* has a significant and negative coefficient as the expectation. This figure shows that the renewable policies implemented by Chinese central and local governments not only support the deployment of renewable energy technology in the domestic market, but also facilitate

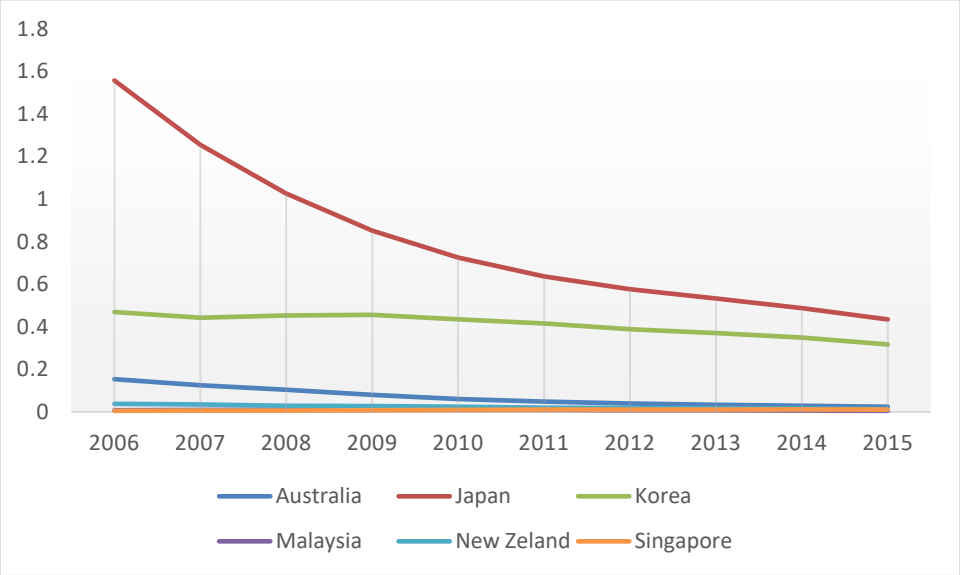
the competitiveness of China's renewable energy commodities in the international market, which as a result increases export efficiency.

The variable *CSEM* also has a significant and positive estimated parameter, as expected, which supports the assumption in the previous section. As the renewable energy market expands, the increased rate of demand for renewable energy commodities in exporting countries may exceed the increase in the corresponding supply. In this case, demand from the international market would be faced with more intensive competition, which leads to decreased trade efficiency. As a result, the faster the expansion of the renewable energy sector in the exporting country, the smaller the relative export value compared to the theoretical trade potential. It can be expected that this kind of trade efficiency loss is not permanent. When the renewable energy sector grows to a certain extent, the increase in the renewable energy market size would represent an increase in the supply of power for both domestic and international markets.

The estimated effect of *CPAT* on u_{it} is positive and significant at a 5 per cent level, which is contrary to the expectation. This paper also uses data on the total enabled patents (*NCPAT*) to substitute *CPAT* to measure the innovation process in China, as a robustness check. The regression result is presented in Table 4.2 column (3), though it does not show a significant difference. Intuitively, more patent evolution in China's renewable energy commodities means that these commodities are relatively more advanced and have better qualities, which should improve their competitiveness in the international market and reduce China's export inefficiency. However, the regression result suggests that the innovation process becomes a trade barrier that reduces the trade efficiency of China's renewable energy commodities exports. One possible explanation is that the growth rate of renewable energy technology innovations in other RCEP countries is faster than that in China, or the number of patents owned by China only accounts for a small part of the total patents. Figure 4.1 shows ratios of the

number of patents owned by importing countries to *CPAT*. Because of data limitations, only six trade partners' data could be collected. It can be seen from Figure 4.1 that all importing countries display a downward trend in this ratio, except Singapore, which is almost unchanged with slight fluctuations. In addition, the value of the ratio in each country ends below 1, which indicates that patents registered in China take a dominant position in bilateral trade, compared to their counterparts. These numbers deny the possibility that the development of renewable energy technologies in China has fallen behind other countries.

Figure 4.4 Ratios of the number of cumulative patents in renewable energy technologies owned by importing countries to China, 2006 to 2015



Source: IRENA Data & Statistics.

This paper explains the negative effect of *CPAT* on trade efficiency by inefficient technical regulations and technology assessment procedures. Because of the barriers caused by different technical standards and the protections of intellectual property, the newly invented patents embodied in China's products may not be approved or deployed in other RCEP countries. Therefore, if China's renewable energy industry increases the supply of new commodities more than old ones, exports to other RCEP

countries will not match such growth in productivity. This trend would significantly deepen the gap between China's theoretical maximum export value and its actual export value. Eventually, the innovation process in China shows as an implicit trade cost and leads to a trade efficiency loss in its exports. This finding indicates an important target for the establishment of RCEP. All members should engage in developing more generally accepted technical regulations, standards, and technology certification systems under the RCEP agreement. This practice will facilitate the technology transfer process within the region, which can effectively reduce the trade inefficiency discussed above.

4.6 Conclusion

It has become the consensus of governments that developing renewable energy technologies is the answer to mitigating climate change and maintaining sustainable growth. Renewable energy is even more important for RCEP countries as they need to balance the surge in energy demand that accompanies economic growth and greenhouse gas emissions. Compared with fossil energy, the development of renewable energy technology is still in early stages. The high initial capital cost is still one of the main barriers to vastly deploying renewable energy power plants and replacing existing fossil energy sources. To reduce construction costs, countries should make full use of the comparative advantages of different trade partners via trade in renewable energy commodities. Governments should focus on how to effectively improve the performance of renewable energy commodities trade, especially on how to reduce the implicit trade cost or improve the trade efficiency; this question remains unexplored in the literature.

This paper used the one-step SFA method and data on China's renewable energy commodities exports to other RCEP countries to identify triggers and barriers in renewable energy commodities trade within the RCEP region. First, the results show that the ETR imposed by China can effectively improve its export values, while tariffs

imposed by importing countries have a significantly opposite effect. This finding suggests that the RCEP countries are pursuing cheaper components as the trade value is sensitive to the changes in price. Second, R&D investment in the renewable energy sector and the size of China's renewable energy market are positively correlated with its exports. However, improving the above factors alone is not sufficient for facilitating China's export.

The estimation results confirm that the implicit trade cost is the main barrier in China's renewable energy commodities exports, as China only realises 29.5 per cent of its export potential to other RCEP countries. One focus of this paper is to figure out which factors can influence the technical inefficiency term. Firstly, the renewable energy policies implemented in China have a significant and negative impact on export inefficiency. This illustrates that supporting policies for renewable energy technologies not only promote the deployment of renewable energy domestically, but also increase the competitiveness of China's commodities in the international market. Secondly, non-tariff barriers in importing countries significantly reduce the trade efficiency score of the renewable energy commodities trade. One thing to notice is that this paper uses the trade openness index as a proxy to capture the effect of non-tariff measurements. However, trade openness is a function of lot of variables, so the proxy might not capture the effects of non-tariff barriers exclusively. Future studies can be conducted on introducing other types of non-tariff barriers measurement.

Although the expansion of China's renewable energy market could increase the export frontier, the estimation results demonstrate that it also has a negative effect on the trade inefficiency term. If China's domestic renewable energy market is growing so fast that increased demand for renewable energy commodities overwhelms increases in supply, exports to other countries will be relatively decreased, though it can be expected that this kind of efficiency loss would not be permanent. Moreover, this kind

of efficiency loss is a signal that the total supply of renewable energy commodities in the RCEP region is far from saturated, as growth in total demand would be faced with more intensive competition. All members should take this chance to facilitate their productivity and export value in renewable energy goods.

Surprisingly, the innovation process in China in the renewable energy sector is found to be positively correlated with trade inefficiency. This paper explains this consequence as being related to inefficient technical regulations and technology certification systems. Because of different technical regulations and standards, newly invented patents in China may not be adopted and deployed by other RCEP members. Therefore, the supply of new renewable energy products in China may not be available for export. As a result, innovation in China shows as an implicit trade cost to its export.

Based on the findings, this paper proposes the following policy implications. To facilitate the import of renewable energy commodities from China, other RCEP countries should, and some have already, actively reduce the corresponding tariffs. When tariff rates for renewable energy goods are gradually reaching zero, the negative effect of non-tariff barriers will become more and more obvious. Therefore, each country needs to investigate which regulations and laws currently in force restrict potential trade in renewable energy. More importantly, all RCEP members should collaborate closely to establish more commonly accepted technical standards to facilitate technology transfer within the region. Labour mobility and trade in service also help promote this process, which should be reinforced by RCEP members. The establishment of RCEP provides a platform for all these implications.

Other RCEP members should learn from China’s experience. As discussed above, the total demand for renewable energy commodities in RCEP region is not fulfilled. This is a good opportunity for all members to increase their exports and let exports lead the development of renewable energy in domestic markets. To achieve this goal,

governments must pay attention to R&D investment in the renewable energy sector. In addition, governments should implement more supporting policies for renewable energies and more stringent environmental regulations. This would accelerate the transition from fossil energy sources to renewable energy sources and increase the competitiveness of the commodities in the international market. Along with growth in renewable energy commodities trade within RCEP area, it is expected that RCEP countries would occupy more market shares in other countries and areas.

4.7 Appendix 4.I

Table 4.3 HS code of renewable energy commodities and descriptions

HS Code	Commodity
382450	Mortars and concretes; non-refractory
382490	Chemical products, preparations and residual products of the chemical or allied industries, n.e.c. or included in heading no. 3824
681091	Cement, concrete or artificial stone; prefabricated structural components for building or civil engineering, whether or not reinforced
700991	Glass mirrors; unframed, excluding rear-view mirrors for vehicles
700992	Glass mirrors; framed, excluding rear-view mirrors for vehicles
711590	Metal; precious or metal clad with precious metal, other than that of item no. 7115.10
730431	Iron or non-alloy steel (excluding cast iron); seamless, cold-drawn or cold-rolled, tubes, pipes and hollow profiles of circular cross-section
730441	Steel, stainless; cold-drawn or cold-rolled (cold-reduced), tubes and pipes of circular cross-section
730451	Steel, alloy (not stainless steel); seamless, cold-drawn or cold-rolled (cold-reduced), tubes, pipes and hollow profiles of circular cross-section
730820	Iron or steel; structures and parts thereof, towers and lattice masts
730900	Reservoirs, tanks, vats and similar containers; for any material (excluding compressed or liquefied gas), of iron or steel, capacity exceeding 300l, whether or not lined or heat insulated
732290	Air heaters and hot air distributors, (not electrically heated), incorporating a motor-driven fan or blower and parts thereof, of iron or steel
741121	Copper; tubes and pipes, of copper-zinc base alloys (brass)
741122	Copper; tubes and pipes, of copper-nickel base alloys (cupro-nickel) or copper-nickel-zinc base alloys (nickel silver)
741129	Copper; tubes and pipes, of copper alloys (other than copper-zinc, copper-nickel base alloys (cupro-nickel) or copper-nickel-zinc base alloys (nickel-silver))
761090	Aluminium; structures (excluding prefabricated buildings of heading no. 9406) and parts of structures, n.e.c. in heading no. 7610, plates, rods, profiles, tubes and the like
761100	Aluminium; reservoirs, tanks, vats and similar containers, for material (not compressed or liquefied gas), of a capacity over 300l, whether or not lined, not fitted with mechanical/thermal equipment
830630	Photograph, picture or similar frames, mirrors; of base metal
840290	Boilers; parts of steam or other vapour generating boilers

840490	Boilers; parts of auxiliary plant, for use with boilers of heading no. 8402 and 8403 and parts of condensers for steam or other vapour power units
840510	Generators; producer gas, water gas, acetylene gas and similar water process gas generators, with or without their purifiers
840681	Turbines; steam and other vapour turbines, (for other than marine propulsion), of an output exceeding 40MW
840682	Turbines; steam and other vapour turbines, (for other than marine propulsion), of an output not exceeding 40MW
840690	Turbines; parts of steam and other vapour turbines
841011	Turbines; hydraulic turbines and water wheels, of a power not exceeding 1000kW
841012	Turbines; hydraulic turbines and water wheels, of a power exceeding 1000kW but not exceeding 10000kW
841013	Turbines; hydraulic turbines and water wheels, of a power exceeding 10000kW
841090	Turbines; parts of hydraulic turbines and water wheels, including regulators
841181	Turbines; gas-turbines (excluding turbo-jets and turbo-propellers), of a power not exceeding 5000kW
841182	Turbines; gas-turbines (excluding turbo-jets and turbo-propellers), of a power exceeding 5000kW
841199	Turbines; parts of gas turbines (excluding turbo-jets and turbo-propellers)
841280	Engines; pneumatic power engines and motors, n.e.c. in heading no. 8412
841290	Engines; parts, for engines and motors of heading no. 8412
841620	Furnaces; furnace burners, for pulverised solid fuel or gas, including combination burners
841861	Heat pumps; other than air conditioning machines of heading no. 8415
841919	Heaters; instantaneous or storage water heaters, non-electric, other than instantaneous gas water heaters
841931	Dryers; for agricultural products, not used for domestic purposes
841939	Dryers; for products n.e.c. in heading no. 8419, not used for domestic purposes
841940	Distilling or rectifying plant; not used for domestic purposes
841950	Heat exchange units; not used for domestic purposes
841960	Machinery; for liquefying air or gas, not used for domestic purposes
841989	Machinery, plant and laboratory equipment; for treating materials by change of temperature, other than for making hot drinks or cooking or heating food
841990	Machinery, plant and laboratory equipment; parts of equipment for treating materials by a process involving a change of temperature
842121	Machinery; for filtering or purifying water

842129	Machinery; for filtering or purifying liquids, n.e.c. in item no. 8421.2
843041	Boring or sinking machinery; self-propelled, n.e.c. in heading no. 8430
843049	Boring and sinking machinery; not self-propelled
847920	Machinery; for the extraction or preparation of animal or fixed vegetable fats or oils
848210	Ball bearings
848220	Bearings; tapered roller bearings, including cone and tapered roller assemblies
848230	Bearings; spherical roller bearings
848240	Bearings; needle roller bearings
848250	Bearings; cylindrical roller bearings n.e.c. in heading no. 8482
848280	Bearings; n.e.c. in heading no. 8482, including combined ball/roller
848340	Gears and gearing; (not toothed wheels, chain sprockets and other transmission elements presented separately); ball or roller screws; gear boxes and other speed changers, including torque converters
850161	Generators; AC generators, (alternators), of an output not exceeding 75kVA
850162	Electric generators; AC generators, (alternators), of an output exceeding 75kVA but not exceeding 375kVA
850163	Electric generators; AC generators, (alternators), of an output exceeding 375kVA but not exceeding 750kVA
850164	Electric generators; AC generators, (alternators), of an output exceeding 750kVA
850231	Electric generating sets; wind-powered, (excluding those with spark-ignition or compression-ignition internal combustion piston engines)
850239	Electric generating sets; (excluding those with spark-ignition or compression-ignition internal combustion piston engines), other than wind powered
850300	Electric motors and generators; parts suitable for use solely or principally with the machines of heading no. 8501 or 8502
850421	Electrical transformers; liquid dielectric, having a power handling capacity not exceeding 650kVA
850422	Electrical transformers; liquid dielectric, having a power handling capacity exceeding 650kVA but not exceeding 10,000kVA
850423	Electrical transformers; liquid dielectric, having a power handling capacity exceeding 10,000kVA
850431	Electrical transformers; n.e.c. in item no. 8504.2, having a power handling capacity not exceeding 1kVA
850432	Transformers; n.e.c. in item no. 8504.2, having a power handling capacity exceeding 1kVA but not exceeding 16kVA
850433	Transformers; n.e.c. in item no. 8504.2, having a power handling capacity

	exceeding 16kVA but not exceeding 500kVA
850440	Electrical static converters
851410	Furnaces and ovens; electric, for industrial or laboratory use, resistance heated
851420	Furnaces and ovens; electric, for industrial or laboratory use, functioning by induction or dielectric loss
851430	Furnaces and ovens; electric, for industrial or laboratory use, other than those functioning by induction, dielectric loss or resistance heated
851490	Furnaces, ovens and heating equipment; parts of the industrial or laboratory equipment of heading no. 8514
854140	Electrical apparatus; photosensitive, including photovoltaic cells, whether or not assembled in modules or made up into panels, light emitting diodes
854390	Electrical machines and apparatus; parts of the electrical goods of heading no. 8543
854442	Insulated electric conductors; for a voltage not exceeding 1000 volts, fitted with connectors
854449	Insulated electric conductors; for a voltage not exceeding 1000 volts, not fitted with connectors
854460	Insulated electric conductors; for a voltage exceeding 1000 volts
890790	Floating structures; tanks, coffer-dams, landing stages, buoys and beacons
900190	Optical elements; lenses n.e.c. in heading no. 9001, prisms, mirrors and other optical elements, unmounted, of any material (excluding elements of glass not optically worked)
900290	Optical elements; n.e.c. in heading no. 9002 (e.g. prisms and mirrors), mounted, being parts or fittings for instruments or apparatus, of any material (excluding elements of glass not optically worked)
900580	Monoculars; other optical telescopes and astronomical instruments, excluding instruments for radio-astronomy
901380	Optical devices, appliances and instruments; n.e.c. in heading no. 9013 (including liquid crystal devices)
901580	Surveying equipment; articles n.e.c. in heading no. 9015, including hydrographic, oceanographic, hydrological, meteorological or geophysical instruments and appliances (excluding compasses)
902610	Instruments and apparatus; for measuring or checking the flow or level of liquids
902620	Instruments and apparatus; for measuring or checking pressure
902680	Instruments and apparatus; for measuring or checking variables of liquids or gases (excluding pressure or the flow and level of liquids and those of heading no. 9014, 9015, 9028 and 9032)
902690	Instruments and apparatus; parts and accessories for those measuring or checking the flow, level, pressure or other variables of liquids or gases

	(excluding those of heading no. 9014, 9015, 9028 or 9032)
902750	Instruments and apparatus; using optical radiations (UV, visible, IR), (other than spectrometers, spectrophotometers and spectrographs)
902830	Meters; electricity supply or production meters, including calibrating meters thereof
903020	Oscilloscopes and oscillographs
903031	Multimeters; for measuring or checking voltage, current, resistance or power, without a recording device
903032	Multimeters; for measuring or checking voltage, current, resistance or power, with a recording device
903033	Instruments and apparatus; for measuring or checking voltage, current, resistance or power, without a recording device (excluding multimeters)
903039	Instruments and apparatus; for measuring or checking voltage, current, resistance or power, with a recording device (excluding multimeters)
903190	Instruments, appliances and machines; parts and accessories for those measuring or checking devices of heading no. 9031

Note: This list is different from the list in Appendix 2.II, as this list covers more categories other than commodities only used in establishing renewable energy power plants.

Chapter 5 Conclusion

5.1 Summary of findings

This thesis, consisting of three empirical research papers, comprehensively and thoroughly investigates trade in renewable energy commodities from a technical efficiency perspective, including the effect of trade on the renewable energy electricity generation sector, trade potential, and triggers and barriers for trade.

The first paper (Chapter 2) finds that investments in renewable energy electricity generation capacity installation in most countries are not efficiently used, though each country's technical efficiency is increasing. The world average technical efficiency ratio in the construction phase increased from 0.422 in 2006 to 0.584 in 2019, and Sweden, China, and Brazil occupied the top three positions. Improving imports in renewable energy commodities and facilitating innovation in the renewable energy sector would effectively reduce the technical inefficiency term. Moreover, R&D investment in the renewable energy power sector in early stages is positively correlated with installed capacity, though it is not directly involved in the construction process. Last and surprisingly, cost reduction does not directly promote newly installed capacity, but it can improve technical efficiency of capacity investment.

The second paper (Chapter 3) divides selected RCEP countries into two groups, based on their renewable energy goods export values, and calculates each country's total trade efficiency (TEM), which consists of the conventional trade efficiency term (TEG) and meta-technology ratio (MTR). The estimation results show that higher export value countries' TEMs are overwhelmingly higher than their counterparts. Differences are mainly caused by significantly higher MTR estimates for the former countries, which demonstrates the presence of technology gap within the RCEP region. In addition, TEG estimates for all countries range from 0.18 to 0.43, which suggests that implicit trade costs are one of the main barriers to trade in renewable

energy commodities.

The third paper (Chapter 4) analyses which factors can influence China's export to the other RCEP countries. First, it reaffirms the conclusion that huge potential exists in trade in renewable energy commodities within the RCEP region. Second, environmental regulations and supportive policies for the renewable energy sector in China are negatively related to the trade inefficiency term. Third, non-tariff barriers reductions in importing countries can effectively improve trade efficiency. Besides, China's renewable energy market size has a mixed effect on its exports. On the one hand, the expansion of China's renewable energy market could directly increase its export values. On the other hand, this expansion would reduce China's export efficiency. Last but not least, the innovations process in China in the renewable energy sector is positively correlated with the trade inefficiency term, which means that it lacks efficient technology transfer systems in the current RCEP cooperation scheme.

5.2 Policy implications

Previous policy instruments, such as feed-in tariffs and feed-in premiums, have been introduced to attract more investment into renewable energy technology, and they have made considerable success. As the total investment in renewable energy technology has reached a significant amount, efficiency of the investment's usage can make a big difference in deploying renewable energy power capacity. Decision makers should switch their focus from increasing renewable energy power generation capacity investment to promoting the efficiency of using capacity investment. This thesis suggests that promoting trade in renewable energy commodities is an effective method to improve investment's performance.

RCEP members should keep their commitments in the RCEP agreement to gradually reduce tariff rates on renewable energy commodities to zero. Meanwhile,

governments should provide export tax rebates for renewable energy goods exports to further reduce the price. However, only focusing on price reduction is not enough. Governments should also pay attention to improving trade efficiency and reducing implicit trade costs. RCEP countries should cooperate more closely to eliminate non-tariff measures, as they have become the main barriers to trade within this region. Moreover, implementing more stringent regulations and policies in the renewable energy sector is likely to increase the competitiveness of renewable energy commodities then to increase export efficiency. In addition, Governments should encourage residents and businesses to use renewable energy generated electricity when applicable, such as providing subsidies for small solar PV panels installed. However, countries may experience an efficiency loss in renewable energy exports during the transition from fossil energy to renewable energy in the short run. Last, RCEP members, which currently have relatively lower export values in renewable energy commodities, need to a create more friendly economic environment for renewable energy investors and make a more generous budget for upgrading their transportation infrastructure and power grid to accommodate trade within this region better.

Innovation in renewable energy technology also plays a role in improving the technical efficiency of capacity investment. However, China’s experience indicates that the transition of the newest renewable energy technologies embodied in its exports is not smooth. RCEP members need to urgently establish more generally accepted technical standards and technology certification systems under the RCEP scheme to free the technology transfer process within the region.

The importance of R&D investment should not be neglected. It does not only increase installed renewable energy electricity capacity, but also trade in renewable energy commodities between RCEP members. Governments, as well as private investors, should keep a faster growth rate of R&D expenditure compared with investment in

renewable energy capacity.

5.3 Limitations and future research

Because of data limitations, this thesis measured the technical efficiency ratio of installing renewable energy power generation capacity in 14 major worldwide investors instead of countries in the RCEP region. If data on capacity investment in RCEP members is available, it would be more persuasive and accurate to evaluate the impact of trade in renewable energy goods within this region.

The second paper adopted concepts of technical efficiency with respect to group frontiers and meta-technology ratio. However, it did not clearly distinguish the differences between those two ratios, though it argues that the technology gap between group frontiers and metafrontier is caused by the inefficiency of the macroeconomic environment. Future studies can be conducted on identifying which factors contribute to TEG and MTR, respectively.

This thesis shows that innovation in renewable energy technology has a significant impact on developing renewable energy sectors. However, it treats the innovation process as an external variable. Exploring the effect of public policies on innovation or how governments can facilitate the innovation process would be a significant extension.

Finally, this thesis mainly analyses the feasibility issue of improvements brought by the establishment of RCEP on renewable energy trade. As the RCEP agreement formally came into force on the 1st of January 2022, with more data becoming available, it would be interesting to evaluate the actual impact of the RCEP agreement on trade in renewable energy commodities.

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