Economic Analysis of Energy Use and Environmental Impacts in Thailand

Panittra Ninpanit

A thesis submitted for the degree of

Doctor of Philosophy of

The Australian National University

July 2019

Declaration

I certify that this thesis is my own work and that, to the best of my knowledge and belief, it contains no material previously included in any other thesis or published work written by another person, except where due reference is made in the text.

P. Ninpanit

Panittra Ninpanit

22 July 2019

Acknowledgements

Writing a thesis is a long and multifaceted process. I would not be able to complete this thesis without great support from many people and organizations. Firstly, I would like to express my deepest gratitude to my supervisor, Professor David Stern, for the enthusiastic and continuous support, invaluable guidance, and understanding. His supervision has encouraged me and enhanced my research and analytical skills considerably throughout my study. Apart from my supervisor, Associate Professor Paul Burke, my advisor, has made a significant contribution to the preparation of this thesis. His comprehensive comments and suggestions have helped me to improve the quality of the research and writing style substantially. I am also thankful to Dr Heinz Schandl, my advisor, for valuable comments and discussions.

For the study in Chapter 2, I am fortunate to have co-authored with scholars from Integrated Sustainability Analysis (ISA) at the University of Sydney: Professor Manfred Lenzen, Dr Arunima Malik, Dr Arne Geschke, and Takako Wakiyama. This research collaboration has broadened my knowledge and experience about multi-regional input-output analysis. I am also grateful to the data providers from the Ministry of Commerce, the Metropolitan Electricity Authority, the Provincial Electricity Authority, the Thai Meteorological Department, the Pollution Control Department, and the Department of Energy. I thank Dr Megan Poore for her editing advice. I also thank the discussants and seminar audience at the Australian National University for useful comments and suggestions to improve the studies in this thesis.

I acknowledge the funding support from the Office of the National Economic and Social Development Board. I would also like to thank the kind and attentive staff at the Office of Educational Affairs in Canberra for their administrative support and helpful advice.

The support and encouragement from my parents are very important to me in the pursuit of this PhD. Finally, I thank Kan Sanchan for his love, support, and patience.

Abstract

This thesis comprises three independent, self-contained empirical studies on energy and environmental issues in Thailand. The first study looks at macroeconomic determinants of energy-related carbon dioxide emissions in Thailand. The analysis is based on a multi-regional input-output database from 1990 to 2010. The study first compares emissions under production-based and consumption-based accounting to examine how international trade plays a role in shaping Thailand's carbon dioxide emissions inventory. It further applies a structural decomposition analysis to break down carbon dioxide emissions into seven accounting-identity determinants: carbon intensity of energy use, energy intensity of output, production recipe, commodity structure of final demand, final demand destination, affluence, and population. The findings suggest that production-based emissions surpassed consumption-based emissions by 23.3% per annum on average. A half of emissions taking place in Thailand was a result of exports while emissions embodied in imports accounted for about one-fifth of total emissions consumed in Thailand. The study also finds that an increase in affluence in Thailand and its exporting countries was the most important factor driving Thailand's emissions to grow.

The second study investigates the relationship between electricity consumption and per capita GDP in Thailand. The key research objective is to find whether the GDP elasticity of electricity demand in Thailand varies with the levels of per capita GDP. The findings can provide useful implications for electricity demand forecasting. Provincial data from 2006 to 2016 and various econometric techniques are used to estimate the electricity-income elasticity in the short run, in five- and ten-year periods, and in the long run. The results suggest that at higher income levels, electricity demand increases more slowly with income. Similar phenomena are observed for residential, non-residential, and total electricity consumption. The findings imply that declining electricity-income elasticity will yield a more precise projection of electricity demand than constant elasticity.

The final study attends to the traffic situation in the Bangkok Metropolitan Region (BMR). It focuses on testing the impact of changes in fuel prices on the concentration levels of three traffic-related air pollutants: carbon monoxide (CO), nitrogen dioxide (NO_2), and particulate matter with a size of less than or equal to 10 microns in diameter (PM_{10}). The data employed are at the daily and monthly basis from 1996 to 2017. The pollution data are collected from 25 monitoring stations across the BMR. The findings provide evidence that higher fuel prices reduce air pollution from road vehicles. The fuel price elasticities of CO and PM_{10} pollution are found to be around –0.3 to –0.4 and –0.1 to –0.4, respectively. The fuel price elasticity of NO_2 is found to be –0.2 to –0.3 during 1996–2006 but the sign changes to be positive afterwards. The substitution of gasoline with gaseous fuels that release more NO_2 potentially caused the fuel price elasticity of NO_2 to change sign after 2006. The results suggest that an elimination of fuel price subsidies will lead to a reduction in air pollution.

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List of Acronyms

$\mu g/m^3$	Micrograms per cubic metre
ADF test	Augmented Dickey-Fuller test
BAU	Business as usual
BMR	Bangkok Metropolitan Region
BOT	The Bank of Thailand
CDD	Cooling degree day
CITEPA	The Interprofessional Technical Centre for Studies on Air Pollution
CNG	Compressed natural gas
CO	Carbon monoxide
CO_2	Carbon dioxide
CPI	Consumer price index
DOPA	Department of Provincial Administration
DPF	Diesel particle filter
EGAT	The Electricity Generating Authority of Thailand
EIA	The U.S. Energy Information Administration
ENCON Fund	Energy Conservation Promotion Fund
EPPO	The Energy Policy and Plan Office
ERC	The Energy Regulatory Commission
ETS	Emission trading scheme
EU	The European Union
F_t	Automatic tariff adjustment
GDP	Gross domestic product
Gg	Gigagram
GHG	Greenhouse gases
GWh	Gigawatt-hour
HC	Hydrocarbons

IEA	International Energy Agency
IMF	The International Monetary Fund
INDC	Intended Nationally Determined Contribution
IPCC	Intergovernmental Panel on Climate Change
IV	Instrumental variable
kg	Kilogram
kWh	Kilowatt-hour
LPG	Liquefied petroleum gas
MEA	The Metropolitan Electricity Authority
mm	Millimetre
MOC	Ministry of Commerce
MOE	Ministry of Energy
MRIO	multiregional input-output
$MtCO_2e$	Million tonnes of carbon dioxide equivalent
NEI	National Emission Inventories
NESDB	Office of the Economic and Social Development Board
NMVOCs	Non-methane volatile organic compounds
NO_2	Nitrogen dioxide
NO_x	Nitrogen oxides
NSO	The National Statistical Office
OLS	Ordinary least squares
PDP	Power development plan
PEA	The Provincial Electricity Authority
Pj	Petajoule
PM	Particulate matter
PM_{10}	Particulate matter with a size of less than or equal to 10 microns in diameter
$PM_{2.5}$	Particulate matter with a size of less than or equal to 2.5 microns in diameter
ppb	Parts per billion

ppm	Parts per million
SBIC	Schwarz's Bayesian information criterion
SDA	Structural decomposition analysis
SRIO	single-regional input-output
Tg	Teragram
TWh	Terawatt-hour
UNECE	The United Nations Economic Commission for Europe
VAT	Value added tax
WHO	World Health Organization

Chapter 1

Introduction

Thailand is facing several energy challenges. Energy use in Thailand grew around 5% per annum on average from 1990 to 2016 while world energy use grew only at 2% (International Energy Agency (IEA), 2018). Thailand's growth in energy use is also higher than its economic growth rate of 4% per annum over the same period (World Bank, 2018). Furthermore, due to its heavy reliance on fossil fuels, Thailand's greenhouse gas emissions have increased hand-in-hand with energy consumption. Apart from greenhouse gases, energy consumption has contributed to local air pollution concerns in many areas of the country (Vichit-Vadakan and Vajanapoom, 2011).

This thesis investigates a range of issues concerning energy challenges in Thailand. It contains three empirical studies examining at these issues with different focuses. In this preliminary chapter, I provide overviews of energy use, energy-related emissions, and relevant policy challenges in Thailand. Next, I discuss the objectives and significance of the empirical studies presented in the following chapters.

1.1 Background information

1.1.1 Energy use in Thailand

Thailand's total primary energy supply (total production + imports – exports – international bunkers + net stock changes) increased from 1,756 petajoules in 1990 to 5,800 petajoules in 2016, or grew around 5% per annum on average (IEA, 2018). The reliance on fossil fuels has been increasing. The share of fossil fuels (coal, natural gas, and oil) in total primary energy supply increased from 64% in 1990 to 78% in 2016. Oil and natural gas are two major energy sources, accounting for 67% of total primary energy supply in 2016. However, the use of natural gas grew much faster than the use of oil. The share of natural gas in total primary energy supply was around 12% in 1990 and increased to 27% in 2016, while the share of oil decline from 42% to 40%. The use of renewable energy excluding biomass has been lower than 1%. Figure 1 presents the quantity and structure of primary energy supply in Thailand from 1990 to 2016.

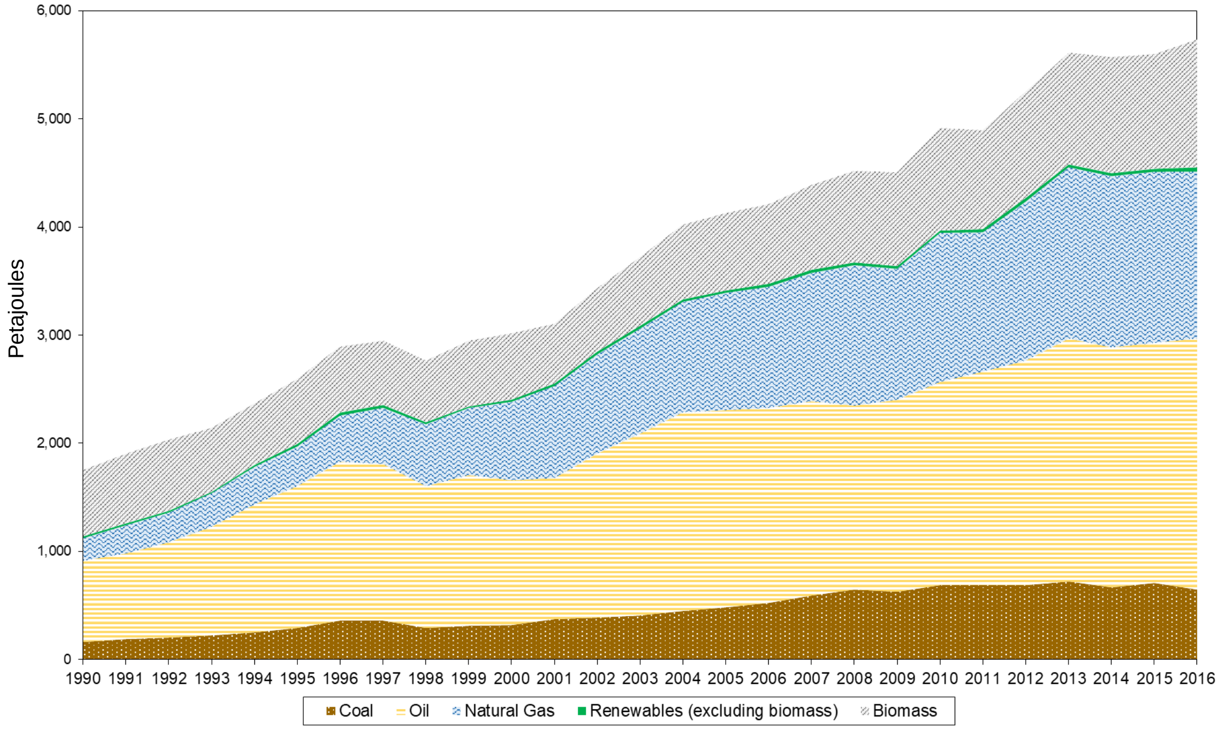

Figure 1.1 Thailand's primary energy supply by fuel 1990–2016. Primary energy supply is energy production plus energy imports, minus energy exports, minus international bunkers, plus net stock changes. Source: IEA (2018).

As presented in Figure 1.2, final energy consumption, or energy consumed by end users, has been dominated by oil products (IEA, 2018). The share of oil increased slightly from 52% in 1990 to 55% in 2016. Biomass was the second-most important energy source in final energy consumption in 1990 but has been replaced by electricity and natural gas over time. The shares of electricity and natural gas in final energy consumption increased from 11% and nearly 0% in 1990 to 17% and 8% in 2016, respectively. The share of natural gas in final energy consumption is significantly lower than in primary energy supply because most of the natural gas supply is used to produce electricity. The role of coal has remained fairly stable.

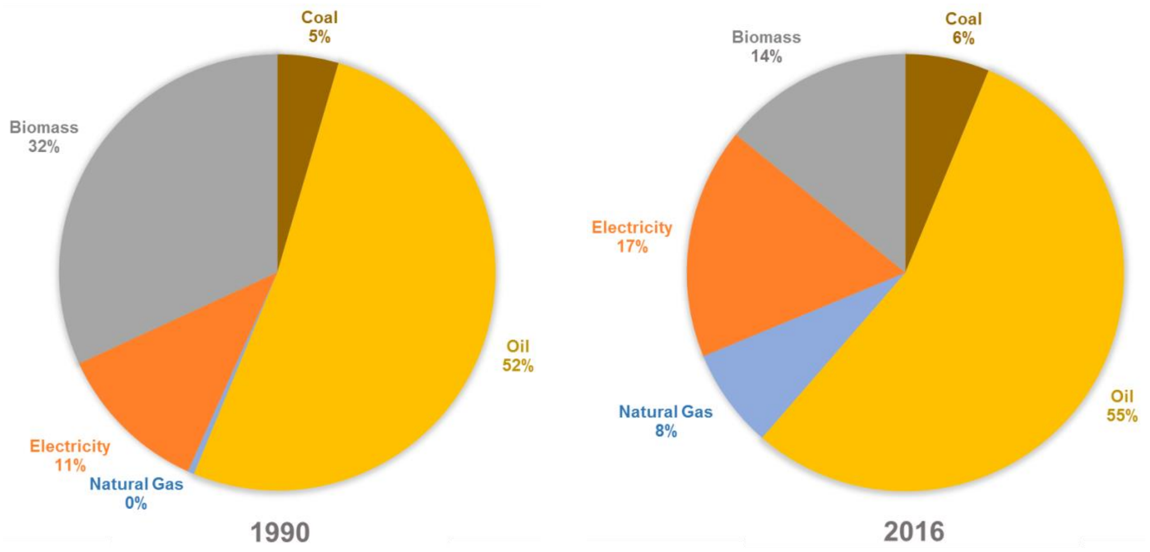

Figure 1.2 Shares of energy sources in Thailand's final energy consumption in 1990 and 2016. Source: IEA (2018).

Figure 1.3 shows that most of the final energy demand in 2016 came from industry and transport (IEA, 2018). Over 1990–2016, industrial energy demand grew approximately 5% per annum on average while transport energy demand grew around 4%. Energy demand from other sectors—residential, agriculture, and commercial and public services—increased much more slowly.

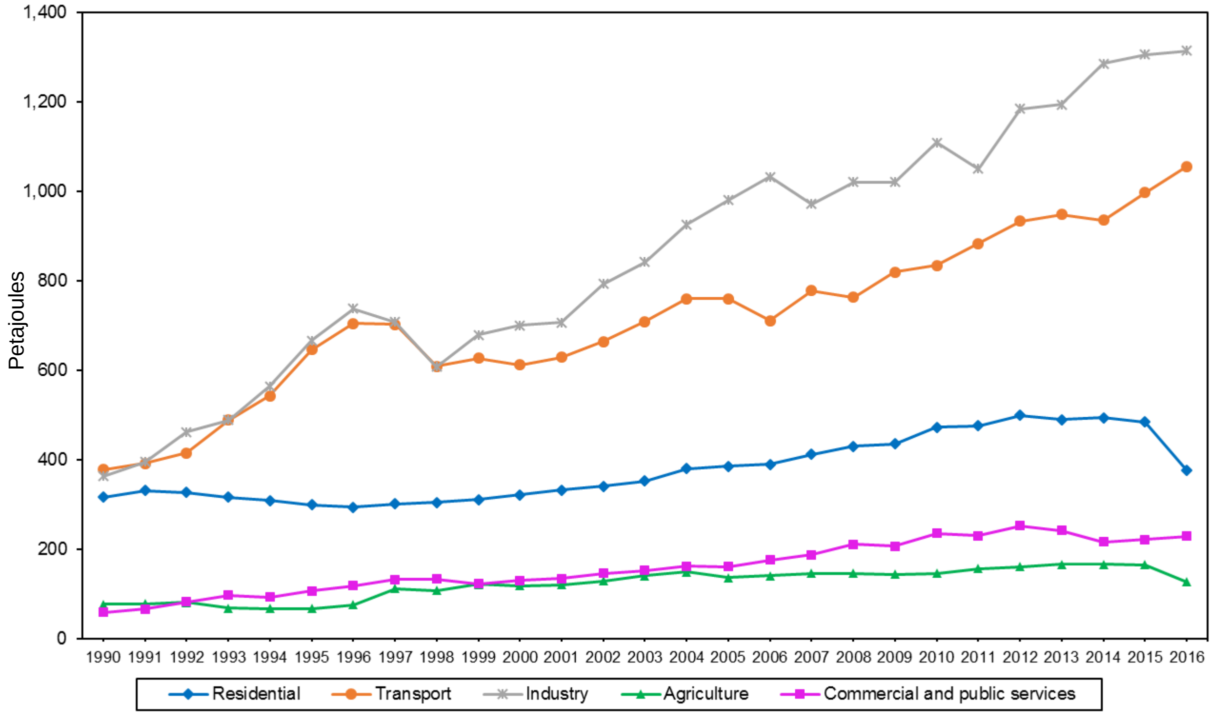

Figure 1.3 Final energy consumption in Thailand by sector 1990–2016. Source: IEA (2018).

1.1.2 Environmental impacts from energy use

1) Greenhouse gases

From Figure 1.4, greenhouse gas emissions in Thailand exhibited a rising trend, grew from around 208 to 440 million tonnes of carbon dioxide equivalent ($MtCO_2e$) over 1990–2016 (World Bank, 2018). This is in contrast to many developed countries where greenhouse gas emissions have been declining for more than a decade, for example, the United Kingdom, Germany, France, and the Netherlands. Carbon dioxide emissions from fuel combustion are responsible for the largest portion of greenhouse gases emitted in Thailand. The share of energy-related carbon dioxide in total greenhouse gas emissions increased from 39% in 1990 to 54% in 2012 (IEA, 2018; World Bank, 2018).

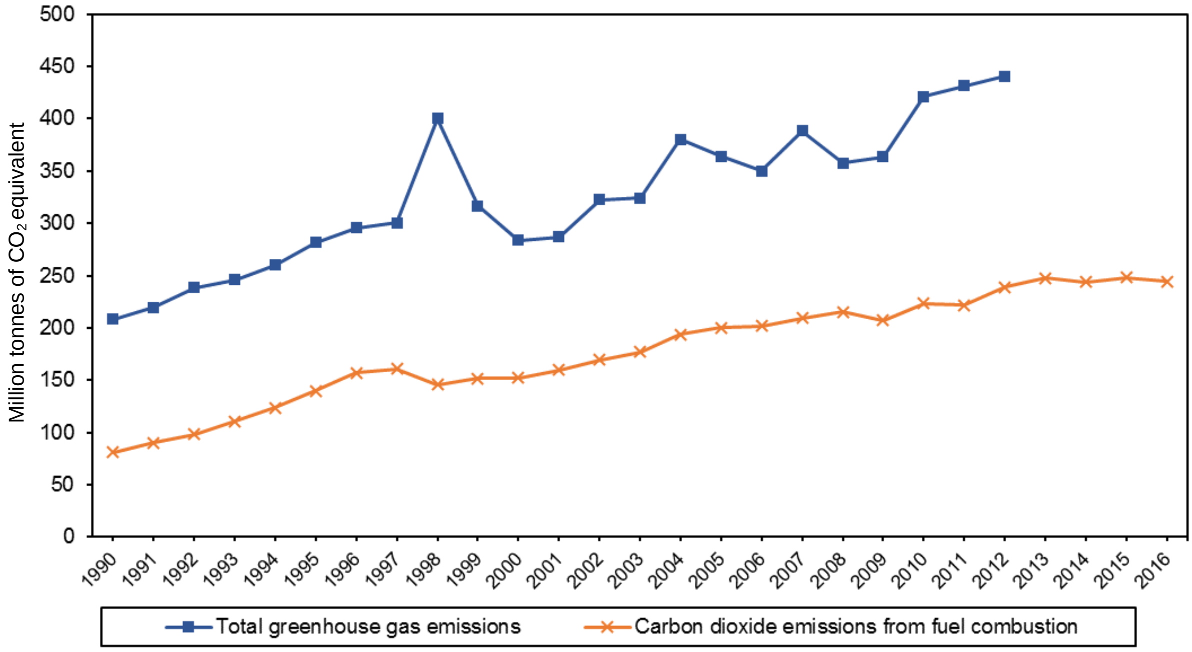

Figure 1.4 Greenhouse gas and carbon dioxide emissions 1990–2016. Greenhouse gas emissions are obtained from the World Bank (2018). Carbon dioxide emissions from fuel combustion are obtained from IEA (2018).

Most of the energy-related carbon dioxide emissions in Thailand are released from electricity generation, transport, and industry. Altogether, these three sources are responsible for more than 80% of total energy-related carbon dioxide emissions. Figure 1.5 shows that in 1990, the amount of emissions from the electricity sector was similar to emissions from transport at around 30 million tonnes while the industry sector released around 15 million tonnes. However, emissions from the electricity sector grew significantly faster than emissions from the other two sectors. In 2016, the electricity sector was responsible for 37% of energy-related carbon dioxide emissions in Thailand. The high contribution of the electricity sector in carbon dioxide emissions and the substantially low renewable energy adoption rate in Thailand tend to suggest that Thailand has the opportunity to reduce a large amount of carbon dioxide emissions by accelerating renewable energy uptake.

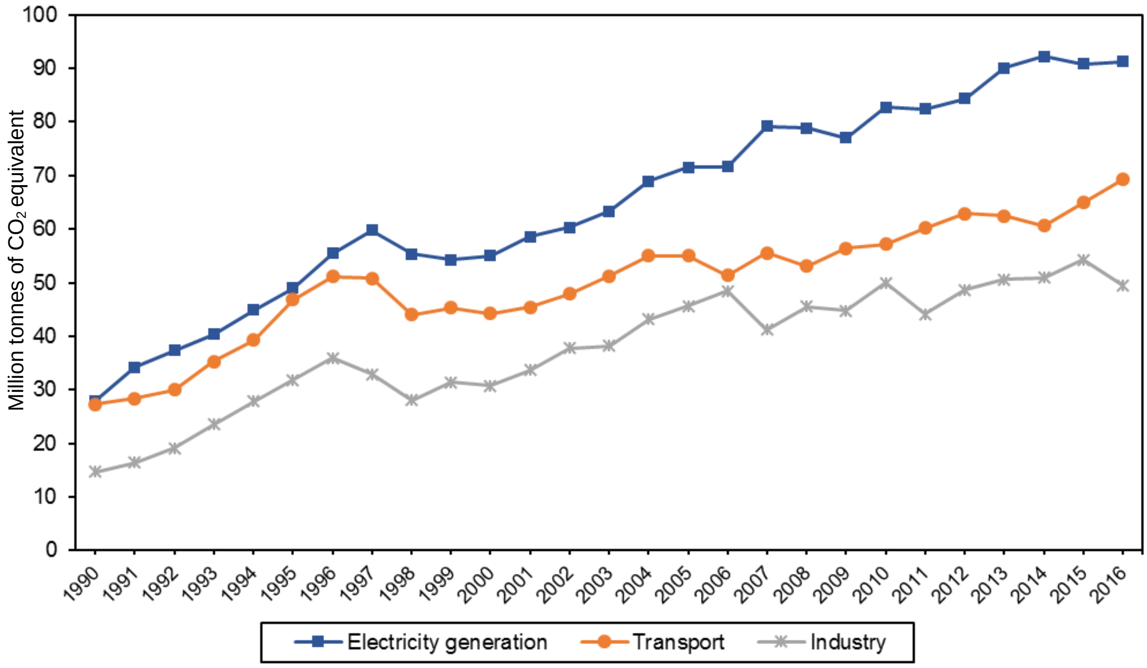

Figure 1.5 Carbon dioxide emissions from fuel combustion by sector 1990–2016. Source: IEA (2018).

Furthermore, Thailand is prone to many climate change impacts such as prolonged drought, severe flooding, sea level rise, declined agricultural yields, and health risks (Marks, 2011). Currently, Thailand is among the top 15 countries worldwide with population exposed to river flood risk (Luo et al., 2015). It is projected that by the year 2030, the population at risk of floods could increase by 204,400 from the year 2010 due solely to climate change (World Resources Institute, 2015).[1]

[1] This number excludes the increased impact of climate change due to socio-economic change. The projection is based on the representative concentration pathway 8.5 and the shared socio-economic pathway 2 from the Intergovernmental Panel on Climate Change 5th Assessment Report.

2) Ambient air pollutants

Nitrogen oxides, sulphur dioxide, carbon monoxide, non-methane volatile organic compounds (NMVOCs), and particulate matter are among air pollutants associated with energy use and can lead to serious adverse health effects (see, for example, Anderson et al. (2012), Chen and Lin (2015), and the Interprofessional Technical Centre for Studies on Air Pollution (CITEPA) (2017)). As presented in Figure 1.6, in 2005, carbon monoxide was released far more than other pollutants, at around 9.5 million tonnes per year (Vongmahadlek et al., 2009). Road transport was the greatest source of carbon monoxide, nitrogen oxides, and NMVOCs emissions.[2] Industry contributed to more than half of sulphur dioxide emissions. Biomass burning played the most important role in the particulate matter 10 emissions.

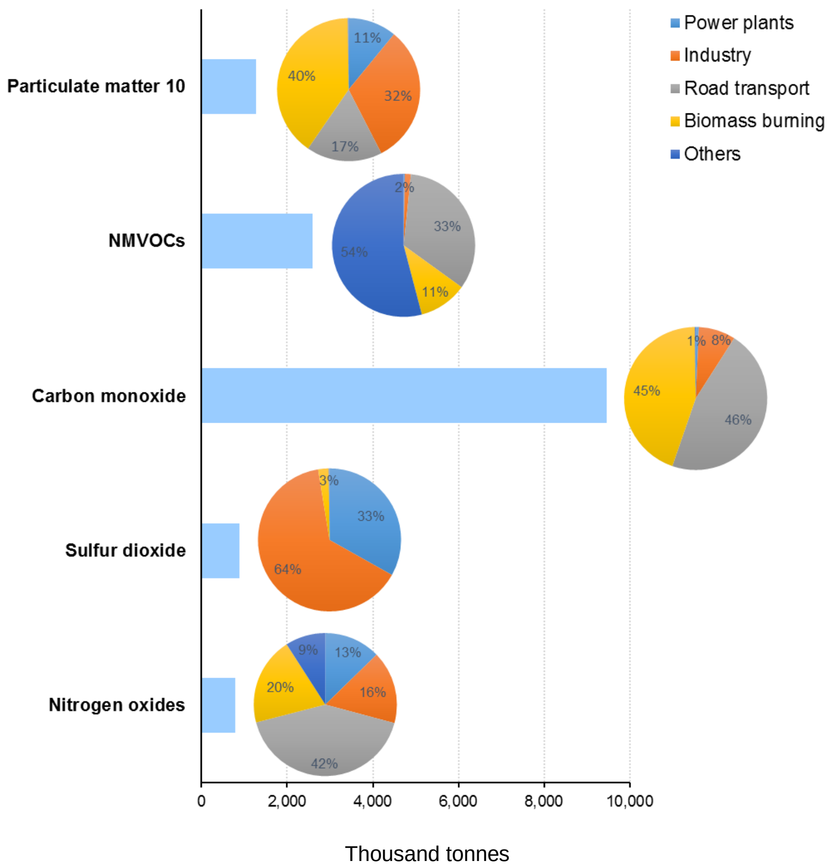

Figure 1.6 Energy-related air pollutants in Thailand and their sources for the year 2005. Source: Vongmahadlek et al., (2009).

[2] Almost all NMVOCs emissions from other sources (apart from power plants, industry, road transport, and biomass burning) arise from vegetation (Vongmahadlek et al., 2009).

1.1.3 Policy challenges

Thailand is confronted with many policy challenges relating to energy use and its environmental impacts. The policy challenges that are relevant to the empirical studies in this thesis are as follows.

1) Greenhouse gas reduction target

According to its Intended Nationally Determined Contribution (INDC), by the year 2030, Thailand intends to reduce its greenhouse gas emissions by 20% from the projected business-as-usual (BAU) level of 555 $MtCO_2e$ (United Nations Framework Convention on Climate Change, 2016). This means that Thailand's greenhouse gas emissions in 2030 should not exceed 444 $MtCO_2e$. As shown in Figure 1.4, Thailand's greenhouse gas emissions already reached 440 $MtCO_2e$ in 2012. To achieve the target, this level of greenhouse gas emissions has to be maintained until 2030.

2) Investment in new power generation capacity

Thailand has a non-competitive electricity market. Electricity supply in Thailand is dominated by the Electricity Generating Authority of Thailand (EGAT), a state-owned enterprise. EGAT is the largest electricity producer and owns 100% of the transmission network nationwide (Sirasoontorn and Koomsup, 2017). Other electricity producers sell electricity to EGAT under long-term power purchase agreements (DBS Group Research, 2017). EGAT subsequently sells the self-produced and purchased power to the two state-owned distribution companies: the Metropolitan Electricity Authority (MEA) and Provincial Electricity Authority (PEA) (Sirasoontorn and Koomsup, 2017).[3] In regard to retail electricity price, Thailand applies the national uniform tariff regulated by the Energy Regulatory Commission (ERC) (Sirasoontorn and Koomsup, 2017).

With this market structure, electricity price does not adjust freely in response to conditions of power demand and supply. As a result, price is not fully capable of providing

[3] MEA and PEA are able to purchase electricity directly electricity producers other than EGAT but limited to only very small power producers with a capacity less than or equal to 10 megawatt (Asian developoment Bank, 2017). These producers shared 3% of power generation in Thailand in 2015 (Sirasoontorn and Koomsup, 2017).

useful information for power generation decisions. In Thailand, the decision to invest in new power generation capacity is regulated by government and based on the power demand forecast as outlined in the power development plan (The Energy Policy and Planning Office, 2015). Therefore, a reliable demand forecast is essential to investment decisions. An underestimated forecast could result in electricity shortages while an overestimated forecast would cause the country to lose the opportunity to use resources for other priorities.

3) Fuel prices

Fuel prices in Thailand are partly controlled via fuel levies. Certain types of fuels such as gasohol blends, diesel, liquefied petroleum gas (LPG), and compressed natural gas (CNG) are often associated with negative levies or price subsidies causing the retail prices to be lower than prices that would be determined by the market (Boonpramote, 2017).[4] The consumption of these fuels, therefore, tends to be higher compared to the case where the price subsidies are not in place. Excessive fuel consumption is associated with several external costs. These include the costs of health impacts resulting from worsening ambient air quality, traffic congestion, and climate change. It is important that policy makers take these external costs into account when determining fuel price intervention measures.

1.2 Research objectives and significance

Each of the three empirical studies in this thesis has specific objectives and seeks to offer useful policy implications related to energy use and environmental impacts in Thailand.

The first study aims to improve our understanding of increasing energy-related carbon dioxide emissions, the most important component of greenhouse gas emissions in Thailand. It starts by evaluating the role of international trade in Thailand’s emissions. International trade accounted for 126% of Thailand’s gross domestic product (GDP) in 2010 (World Bank, 2018). The study also examines the determinants that drove the emissions to grow over the past few decades. The results provide insights into the size of changes in emissions driven by economic conditions such as economic growth and structural change, as well as policy-

[4] Thailand recently removed price controls on CNG in 2016 and transport LPG in 2017 (The Nation, 2016; and Bangkok Post, 2017).

related phenomena including energy efficiency improvement and fuel transition. The findings can assist policy makers in assessing the effectiveness of climate policy in the past and design policy measures to ensure that emissions the reduction target in 2030 will be met.

The second study examines the relationship between electricity demand and economic growth. This study estimates the electricity-GDP elasticity or the degree to which electricity demand grows with GDP, which is useful information for electricity demand forecasts. In this study, I also tests the possibility that the degree of dependence of electricity demand on GDP is different for different GDP levels. If that is the case suggested by the findings, the electricity demand forecast will likely be improved by using GDP-varying elasticity.

The third study investigates the effect of transport fuel prices on traffic-related air pollution by using the Bangkok Metropolitan Region (BMR) as the study area. The BMR is an area with high traffic density and has suffered from unhealthy air quality for many years (Vichit-Vadakan et al., 2010; Vichit-Vadakan and Vajanapoom, 2011). The estimates of fuel price elasticity of air pollution in this study can provide ideas as to what extent air quality in the BMR could improve by removing fuel price subsidies or increasing fuel taxes. Although the connection between fuel prices and traffic pollution might decline in the future when electric vehicle uptake is pervasive, the results of this study can give a clue about traffic demand response in respect to changes in the price of electric power.

1.3 Thesis structure

This thesis consists of five chapters. Following the introduction chapter, Chapters 2–4 are the core chapters, containing three empirical studies as outlined above. Chapter 2 presents the study on Thailand’s energy-related carbon dioxide emissions from 1990 to 2010 using a multi-regional input-output database. The study in Chapter 3 investigates the GDP elasticity of electricity demand in Thailand by employing provincial data from 2006 to 2016. Chapter 4 presents the research exploring the impact of changes in fuel prices on air quality in the BMR. In this study, I use both daily and monthly from 1996 to 2017. Finally, Chapter 5 provides conclusion of the thesis by summarizing key findings of the empirical studies and discussing policy implications obtained from the findings.

Chapter 2

Thailand's energy-related carbon dioxide emissions from production-based and consumption-based perspectives[5]

2.1 Chapter overview

Over the past few decades, Thailand has been one of the highly open economies and one of the most successful countries in applying the export-led growth model. At the same time, carbon dioxide (CO_2) emissions released in Thailand tripled between 1990 and 2010. To examine how international trade plays a role in shaping Thailand's CO_2 emissions inventory, we compare emissions under both production-based and consumption-based accounting over 1990–2010 and disaggregate energy-related CO_2 emissions into traded and non-traded parts. We also use a multi-regional input-output database for performing a structural decomposition analysis (SDA) to investigate the factors contributing to changes in CO_2 emissions. We find that Thailand continually stood out as a net carbon exporting country. CO_2 embodied in exports accounted, on average, for 46.0% of domestically produced emissions. Our SDA results suggest that traded and non-traded emissions grew mainly due to increasing per-capita consumption in Thailand and abroad. Improvements in energy efficiency played an important role in decelerating emissions growth in Thailand. However, the impact was less than half of the accelerating effect of per-capita consumption.

[5] This study is a multi-authored paper where I am the lead author. The other authors include Arunima Malik, Takako Wakiyama, Arne Geschke, and Manfred Lenzen from Integrated Sustainability Analysis (ISA) at the University of Sydney. In this study, I developed the research framework, prepared part of the data, carried out the analysis, and wrote the paper. The other authors contributed to the data preparation, code writing, supervision of the research team, and editing the paper. This paper has been submitted to Energy Policy and is now under revision for a resubmission.

2.2 Introduction

Production-based and consumption-based accounting are the two accounting approaches commonly used to calculate national CO_2 emissions (Lenzen et al., 2007; Peters, 2008; Davis and Caldeira, 2010; Blanco et al., 2014). Emissions calculated using the production-based approach are generated from activities taking place within the national territory. The production-based approach therefore includes emissions from the production of goods consumed domestically and goods exported to all other countries. The consumption-based approach, on the other hand, assigns emissions embodied in the production of exports to the consuming countries (Lenzen et al., 2007; Peters, 2008). Currently, production-based accounting is stipulated by the Intergovernmental Panel on Climate Change (IPCC) guidelines for calculating the National Emission Inventories (NEI) that indicate how much greenhouse gases each nation is responsible for. However, it is argued that the production-based NEI can result in the reallocation of production to countries where mitigation policies are less stringent or 'carbon leakage' (Peters and Hertwich, 2008b; Jakob and Marschinski, 2013), and that the consumption-based accounting can solve this problem (Peters, 2008; Peters and Hertwich, 2008; Peters, 2010; Barrett et al., 2013).

Although the consumption-based approach is superior when it comes to addressing carbon leakage, it yet has certain disadvantages as discussed by Munksgaard et al. (2000), Peters (2008), Barrett et al. (2013), Jakob & Marschinski (2013), Kander et al., (2015), and Afionis et al. (2017). One of the key issues is that, under a consumption-based accounting regime, a country is liable for emissions taking place in areas over which it has no jurisdiction. The country, therefore, lacks the authority to implement mitigation policies over such emissions. As a result, a number of studies propose consumption-based emissions to be used as a complementary indicator to the conventional production-based emissions (e.g., Wiedmann, 2009; Peters, 2010; Barrett et al., 2013).

In this study, we investigate Thailand's CO_2 emissions over 1990–2010 from both production-based and consumption-based perspectives. We base our analysis on multiregional input-output (MRIO) data from the Eora database (Lenzen et al., 2012, 2013). In order to directly relate changes in CO_2 emissions to changes in energy use, we limit our CO_2 emissions data to emissions resulting from fuel combustion only. CO_2 from fuel combustion is the largest source of greenhouse gases (GHG) emissions in Thailand, accounting for 66% of total GHG emissions in 2011 (Office of Natural Resources and Environmental Policy and Planning, 2015 p.30).[6]

Our choice of Thailand as a case study is based on three main reasons. First, over 1990–2010, Thailand's CO_2 emissions from fuel combustion increased about threefold, at twice the world-average growth rate (IEA, 2018). Second, Thailand is a highly open economy. Its degree of trade openness[7] in 1990 was already very high at 76% (compared to 35% for overall middle income countries), but even increased to 127% in 2010, while the overall number for middle-income countries is considerably lower at 50% (World Bank, 2018). We hypothesize that its heavy involvement in international trade strongly influenced Thailand's emissions profile. Finally, although studies providing elaborate analysis on energy use and emissions in Thailand have been executed by, for example, Limmeechokchai and Suksuntornsiri (2007), Supasa et al. (2016), Kunanuntakij et al. (2017), Supasa et al. (2017a), and Supasa et al. (2017b), these studies apply single-regional input-output (SRIO) analysis, which assumes that imported products are produced with the same technology as corresponding domestic products.[8] The MRIO model employed in this paper, on the other hand, differentiates technical coefficients of imports from domestic technical coefficients, and captures the differences in technical coefficients of imports from different trading partners (Lenzen et al., 2004; Wiedmann, 2009). Also, the MRIO model can take into account feedback effects in the global supply chains (changes in final demand in

[6] Total GHG used to calculate the share of CO_2 from fuel combustion does not include GHG removal from land-use change and forestry. If the GHG removal is taken into account, the share of CO_2 from fuel combustion in total GHG will be 86%.

[7] The ratio of the summation of total imports and exports to GDP.

[8] Su and Ang (2011, 2013) show that it is possible to link the SRIO model with bilateral trade data to differentiate technical coefficients of imports from domestic technical coefficients but this approach has not been applied in studies focusing on Thailand as listed above. Nevertheless, unlike the MRIO model, this approach only captures the final stage of an international supply chain of imports rather than the entire chain of the production (Wiedmann et al., 2007b).

one country resulting in changes in intermediate demand in other countries) (Wiedmann et al., 2007; Su and Ang, 2011).

To highlight the influence of international trade on emissions inventories, we split production-based and consumption-based carbon emissions into traded (imported or exported) and non-traded (domestic) parts. This allows us to categorize CO_2 emissions based on where the emissions take place and the sources of final demand that drive emissions. We then apply structural decomposition analysis (SDA) to investigate the factors determining each part of emissions. Using SDA, we break down CO_2 emissions into seven determinants in the form of an accounting identity: carbon intensity of energy use, energy intensity of output, production recipe, commodity structure of final demand, final demand destination, affluence or final demand per capita, and population. The fact that SDA makes use of input-output tables allows us to capture indirect demand effects, spillover effects occurring when an increase in direct demand (final demand) in one sector and/or country results in an increase in the demand for inputs produced from other sectors and/or countries (intermediate demand). This methodology has been extensively applied to study environmental changes mostly in two areas: energy consumption (e.g., Rose and Chen, 1991; Wachsmann et al., 2009; Zhang and Lahr, 2014; Lan et al., 2016; Wang et al., 2017; Croner and Frankovic, 2018) and CO_2 as well as other greenhouse gases (e.g., Rørmose and Olsen, 2005; Peters et al., 2007; Wood, 2009; Minx et al., 2011; Su and Ang, 2012; Malik and Lan, 2016; Malik et al., 2016; Jiang and Guan, 2017).

Our study is not the first to estimate consumption-based emissions and emissions embodied in international trade for Thailand. Peters and Hertwich (2008b), Davis and Caldeira (2010), and Wiebe and Yamano (2016) calculated consumption-based emissions for several countries including Thailand. Peters and Hertwich (2008b) also calculated emissions embodied in trade for those countries. However, their studies only provide estimates for one or two years: 2001 for Peters and Hertwich (2008b), 2004 for Davis and Caldeira (2010), and 1995 and 2011 for Wiebe and Yamano (2016). Our study provides time-series analysis from 1990 to 2010. In addition, we go further to explain changes in traded and non-traded emissions using SDA.

Our findings suggest that over 1990–2010 emissions embodied in Thailand's exports always exceeded emissions embodied in its imports: Each year, production-based emissions surpassed consumption-based emissions by about 23.3%. We also find that an increase in production-based and consumption-based emissions was driven mostly by the accelerating impact from demand-side effects, especially the affluence effect, and could not be fully offset by an improvement in production technology. However, compared to consumption-based emissions, production-based emissions were affected more by the economic prosperity but less by the technological improvement. Our SDA results of traded and non-traded emissions also reveal interesting insights about the role of international trade in Thailand's emission inventory.

The following section presents the methodology we use to estimate traded and non-traded emissions and carry out SDA. Next, Section 2.4 discusses our data. Section 2.5 provides results. Finally, Section 2.6 concludes and discusses policy implications.

2.3 Methodology

2.3.1 Environmental input-output analysis

Input-output models assume a linear relationship between output and final demand in such a way that a sector uses inputs in fixed proportions over a given accounting period.[9] In input-output models, the total output of sector *i* consists of two parts: (1) intermediate output, which is used as input in other sectors, and (2) final output, which is destined for final consumption. In an economy with *n* sectors, this relationship can be written as

$$\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{y} , \tag{2.1}$$

[9] In SDA analysis, the assumption of fixed proportions of inputs is partly relaxed because SDA uses data from input-output tables from different years so the proportions of inputs are allowed to vary between years (Hoekstra and van den Bergh, 2003).

where $\mathbf{x}$ is an $n \times 1$ vector of gross outputs, $\mathbf{A}$ is an $n \times n$ matrix of technical coefficients or direct requirement, $\mathbf{y}$ is an $n \times 1$ vector of final demand. Each element of matrix $\mathbf{A}$, a_{ij}, represents a ratio of the value of product from sector i used by sector j to the value of total output of sector j. For detailed discussions of input-output model, please see Miller and Blair (2009).

After solving for gross output, Equation (2.1) can be rewritten as

$$\mathbf{x} = (\mathbf{I}-\mathbf{A})^{-1}\mathbf{y} = \mathbf{L}\mathbf{y} \tag{2.2}$$

where $\mathbf{I}$ is an identity matrix. The term $(\mathbf{I}-\mathbf{A})^{-1}$ or $\mathbf{L}$ is usually referred to as the 'Leontief inverse'. This term reflects interrelations between various economic sectors. It can capture how each sector changes its intermediate input structure (production recipe) or its requirements from other sectors used in the production process.

To account for pollution generated from economic activities, environmental input-output analysis assumes that pollution is a proportion of output value (Casler and Rose, 1998; Miller and Blair, 2009; and Baiocchi and Minx, 2010). Let $\mathbf{q}$ be a $1 \times n$ row vector of CO_2 emissions intensity or emissions per unit of output in each sector. Total CO_2 emissions, Q, thus, can be shown as

$$Q = \mathbf{qLy}. \tag{2.3}$$

According to Equation (2.3), Q is a function of final demand; it represents the total emissions generated by the economy in supporting final demand both directly (emissions arising from output required for final consumption) and indirectly (emissions arising from output required for intermediate consumption) (Miller and Blair, 2009).

2.3.2 Estimating traded and non-traded emissions

From Equation (2.3), the environmental input-output analysis is associated with three elemental matrices: **q**, **L**, and **y**. In an MRIO-based model, these matrices must contain data for the entire world. In particular, the **L** matrix contains information of technical coefficients of both domestic and international production. Consequently, using an MRIO database allows us to take into account the emissions embodied in domestic and global supply chains (Lenzen et al., 2004).

To derive SDA models pertinent to Thailand's traded and non-traded emissions, we modify the spatial decomposition method used by Lan et al. (2016). Lan et al. (2016) uses the spatial decomposition to decompose consumption-based energy use of a particular country (total energy embodied in the production of products consumed within the country) into domestic energy footprint (energy embodied in the production taking place within the country) and rest-of-world energy footprint (energy embodied in the production taking place in other countries). In this study, we apply the spatial decomposition to decompose Thailand's production-based CO_2 emissions into exported emissions (CO_2 emissions embodied in the production taking place in Thailand to produce exported products) and domestic emissions (CO_2 emissions embodied in the production taking place in Thailand to produce domestically consumed products), and decompose the consumption-based CO_2 emissions into domestic emissions and imported emissions (carbon embodied in the production taking place outside Thailand to produce the products that are consumed in Thailand.[10] Similar approaches have also been applied by Peters and Hertwich (2008a), Kanemoto et al. (2014), and Malik and Lan (2016).

We start by splitting the **q** and **y** matrices into Thailand's part and the rest of the world's part (labelled with THA and ROW subscripts respectively in Figure 2.1). For production-based carbon emissions, we maintain the full **L** and **y** matrices, but assign zeroes to the rest of the world's part in the **q** matrix. This means we ignore emissions taking place in other countries but take into account the fact that emissions occurring in Thailand are partly driven by final demand

[10] Imported emissions in this study is similar to rest-of-world footprint in Lan et al. (2016).

from other countries. The SDA model for production-based emissions (Q_{PB}) can be expressed as:

$$Q_{\mathrm{PB}} = \mathbf{q}_{\mathrm{THA}}\mathbf{L}_{\mathrm{World}}\mathbf{y}_{\mathrm{World}} \tag{2.4}$$

where $\mathbf{q}_{\mathrm{THA}}$ is the CO_2 intensity for Thailand, $\mathbf{L}_{\mathrm{World}}$ is the Leontief inverse for the world, and $\mathbf{y}_{\mathrm{World}}$ is the global final demand.

For the consumption-based analysis, the **q** matrix includes emissions occurring in all countries, but in the **y** block, final consumption of other countries is converted to zeroes. The consumption-based model, thus, includes emissions taking place anywhere in the world driven solely by final demand from Thailand. Consumption-based emissions (Q_{CB}) can be written as

$$Q_{\mathrm{CB}} = \mathbf{q}_{\mathrm{World}}\mathbf{L}_{\mathrm{World}}\mathbf{y}_{\mathrm{THA}} \tag{2.5}$$

We further decompose the production-based and consumption-based emissions in order to differentiate non-traded emissions from traded emissions as shown in Figure 2.1. Production-based emissions are decomposed into exported emissions (Q_{EE}) and domestic emissions (Q_{DE}). Similarly, consumption-based emissions are decomposed into Q_{DE} and imported emissions (Q_{IE}). Q_{EE} is derived by revoking only Thailand's part in the **q** matrix and the rest of the world's part in the **y** matrix.[11] Q_{DE} is derived by revoking only Thailand's part is in both **q** and **y** matrices. Finally, Q_{IE} is derived by revoking only the rest of the world's part in the **q** matrix and Thailand's part in the **y** matrix. The SDA equations for Q_{EE}, Q_{DE}, and Q_{IE} can be written as follows.

[11] Because Q_{EE} considers only emissions that actually take place in Thailand, it does not include emissions embodied in intermediate goods that Thailand imports to produce its final products exported to other countries. Similary, Q_{DE} does not cover emissions embodied in imported intermediate goods used for producing goods consumed in Thailand. However, it does cover emissions generated in Thailand because of the production of exported intermediate goods which are subsequently imported back to Thailand as final products.

$$Q_{EE} = \mathbf{q}_{\mathrm{THA}}\mathbf{L}_{\mathrm{World}}\mathbf{y}_{\mathrm{ROW}} \tag{2.6}$$

$$Q_{DE} = \mathbf{q}_{\mathrm{THA}}\mathbf{L}_{\mathrm{World}}\mathbf{y}_{\mathrm{THA}} \tag{2.7}$$

$$Q_{IE} = \mathbf{q}_{\mathrm{ROW}}\mathbf{L}_{\mathrm{World}}\mathbf{y}_{\mathrm{THA}} \tag{2.8}$$

This approach gives Q_{EE} and Q_{DE} that are mutually exclusive and collectively exhaustive representations of production-based emissions. Likewise, Q_{DE} and Q_{IE} are mutually exclusive and collectively exhaustive representations of consumption-based emissions.

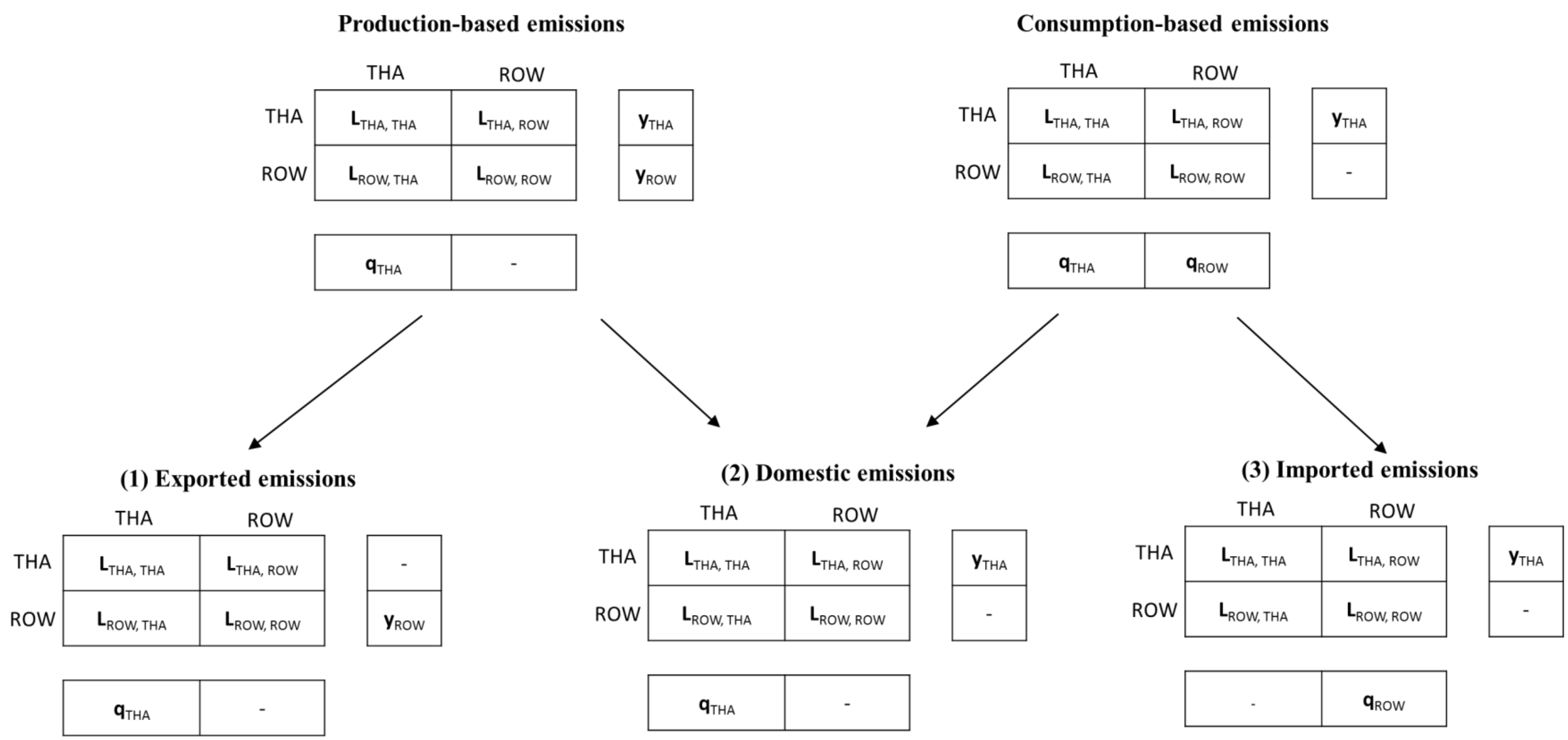

Figure 2.1 MRIO-based spatial decomposition of production-based and consumption-based emissions. Notes: THA and ROW denote Thailand and the rest of the world, respectively. Each cell represents a block matrix in MRIO structure. **q** is CO_2 emissions intensity (CO_2 emissions per unit of output) block with dimension of $1 \times n$. **L** is Leontief inverse block with dimension of $n \times n$, **y** is final demand block with dimension of $n \times 1$, where n is number of sectors.

2.3.3 SDA models

To derive our SDA formulation, we further decompose **q** and **y** in Equation (2.3) as follows. We decompose **q** into two determinants: (1) CO_2 intensity of energy use or fuel mix: $\mathbf{c} = (c_j)_{1\times n}$, and (2) energy intensity: $\hat{\mathbf{e}} = (e_{ij})_{n\times n}$ where **c** is a vector of CO_2 emissions per unit of energy use and $\hat{\mathbf{e}}$ is a diagonalized vector of energy use per unit of output. For **y**, rather than using final demand in a vector form, in our analysis final demand is in a matrix form with dimension of $n \times m$ where m is final demand destinations, consisting of final consumption destinations (household final consumption, non-profit institution final consumption, and government final consumption) and investment destinations (gross-fixed capital, changes in inventory, acquisitions less disposals of valuables). This allows us to decompose our final demand into four determinants: (1) commodity structure of final demand: $\mathbf{u} = (u_{ij})_{n\times m}$, (2) destination structure of final demand: $\mathbf{v} = (v_i)_{m\times 1}$, (3) final demand per capita: $y_{1\times 1}$, and (4) population: $P_{1\times 1}$. Each element of **u** represents the share of final demand of one sector from one final demand destination in the total final demand of all sectors from the same final demand destination. Each element of **v** is the share of final demand of each final demand destination in total final demand. The decomposition formula then becomes

$$\mathrm{Q} = \mathbf{c}\hat{\mathbf{e}}\mathbf{L}\mathbf{u}\mathbf{v}yP \tag{2.9}$$

We apply an additive SDA, which decomposes changes in Q from time 0 to t into the summation of changes of its determinants weighted by values of other determinants in time 0 or t as presented in Equation (2.10). The basics of additive SDA are discussed in detail in (Miller & Blair 2009, p.593-598).

$$\Delta\mathrm{Q} = \underbrace{\Delta\mathbf{c}\hat{\mathbf{e}}\mathbf{L}\mathbf{u}\mathbf{v}yP}_{\substack{\text{Fuel mix effect} \\ \text{(change in CO}_2 \\ \text{intensity of energy use)}}} + \underbrace{\mathbf{c}\Delta\hat{\mathbf{e}}\mathbf{L}\mathbf{u}\mathbf{v}yP}_{\substack{\text{Energy intensity} \\ \text{effect}}} + \underbrace{\mathbf{c}\hat{\mathbf{e}}\Delta\mathbf{L}\mathbf{u}\mathbf{v}yP}_{\substack{\text{Production} \\ \text{recipe effect}}} + \underbrace{\mathbf{c}\hat{\mathbf{e}}\mathbf{L}\Delta\mathbf{u}\mathbf{v}yP}_{\substack{\text{Final demand} \\ \text{structure effect}}} + \underbrace{\mathbf{c}\hat{\mathbf{e}}\mathbf{L}\mathbf{u}\Delta\mathbf{v}yP}_{\substack{\text{Final demand} \\ \text{destination effect}}} + \underbrace{\mathbf{c}\hat{\mathbf{e}}\mathbf{L}\mathbf{u}\mathbf{v}\Delta yP}_{\substack{\text{Affluence} \\ \text{effect}}} + \underbrace{\mathbf{c}\hat{\mathbf{e}}\mathbf{L}\mathbf{u}\mathbf{v}y\Delta P}_{\substack{\text{Population} \\ \text{effect}}} \tag{2.10}$$

In the derivation of this additive SDA formulation, it can be shown that there are several possible forms of decomposition because each variable multiplying with the Δ-terms can take the value of either time 0 or *t*. This leads to a problem called '*non-uniqueness*'. To deal with the non-uniqueness problem, we select a method proposed by Dietzenbacher & Los (1998), usually referred to as the D&L method. This method calculates the mean of coefficients in all possible decomposition forms.[12] Su & Ang (2012) suggest that the D&L method is one of the preferable SDA methods because it gives ideal decomposition: the results do not contain residual and pass the factor-reversal test.

It is important to note that although Q_{EE} and Q_{DE} add up to production-based emissions, estimates of the same SDA component of Q_{EE} and Q_{DE} do not necessarily add up to an estimate of that SDA component of production-based emissions. For example, a summation of fuel mix effect of Q_{EE} and Q_{DE} may not be equal to a fuel mix effect of production-based emissions. The same applies to Q_{DE} and Q_{IE}.

2.4 Data

We use the MRIO data obtained from the Eora database. Eora provides annual time series of MRIO with 26 common sectors (Eora26). The database is available online at www.worldmrio.com. We include MRIO data of 186 countries. Lists of sectors and countries are provided in Appendix A.1 and A.2. The Eora MRIO incorporates several types of data from different sources, e.g., national input-output tables from national statistical offices, the UN national accounts, the UN Comtrade database, and the UN Service Trade database. These data are used as constraints in the optimization process for balancing Eora MRIO. The techniques used to build Eora MRIO and characteristics of the dataset are discussed in detail by Lenzen et al. (2012) and Lenzen et al. (2013). Similar to other MRIO databases, Eora output is subjected to a certain degree of uncertainties, and there tends to be some variation in consumption-based carbon and SDA estimates generated from different MRIO databases due

[12] Dietzenbacher & Los (1998) show that the number of all possible decomposition forms equals *n*! where *n* is the number of determinants. However, instead of calculating all 7! = 5,040 decomposition forms, which are cumbersome, we apply a technique developed by Rørmose & Olsen (2005) to reduce the calculation time. This technique was shown to give the same results to the original D&L method.

largely to heterogeneity in raw data used and construction techniques (Moran and Wood, 2014; Owen et al., 2014; Rodrigues et al., 2018).

Although the Eora26 MRIO has lower sector detail than the full Eora (the number of sectors in the full Eora varies by countries; 180 sectors in the case of Thailand), the common sector classification of Eora26 helps to maintain consistency of the SDA effects between countries, especially the effects associated with number of sectors such as the production recipe effect and the final demand structure effect. One disadvantage of sector aggregation is that it may bring additional uncertainties to the results (Lenzen et al., , 2004, 2010; Weber, 2008; Su et al., 2010;).

The Eora MRIO is more suitable for this study than other MRIO databases such as the World Input–Output Database (WIOD; Timmer et al., 2015) and EXIOBASE (Tukker et al., 2013) where Thailand is merged into the rest of the world. Other databases that have Thailand as an independent region either provide data only for certain years (e.g., the Global Trade Analysis Project (GTAP; Andrew and Peters, 2013), the Global Resource Accounting Model (GRAM; Bruckner et al., 2012), and IDE-JETRO (Meng et al., 2013)), or provide annual time series data for a shorter period (e.g., The OECD Inter-Country Input-Output (ICIO) Tables (OECD, 2017)). Owen et al., (2014) provide a comparison between Eora's key features and those of GTAP and WIOD.

The energy consumption data are obtained from the International Energy Agency (International Energy Agency, 2018) in terajoules. The energy data cover eight groups of primary energy sources: (1) natural gas, (2) coal, (3) petroleum, (4) nuclear, (5) hydro, (6) geothermal, (7) solar, wind, and other renewables and (8) biomass and waste.[13] The energy data are presented in terajoules. CO_2 emissions in gigagrams (Gg) are converted from the energy data using CO_2 emissions factors provided by IPCC (2017). To link the energy and CO_2 emission data with the MRIO data, we construct a concordance matrix to transform energy and CO_2 emissions data into the 26 common sectors of Eora. The concordance matrix is presented in Appendix A.3. Population data are obtained from the World Bank (2018). To

[13] Non-energy use such as the use of oil as petrochemical materials is not included.

remove the effect of inflation, we deflate current monetary values in MRIO to constant 2000 US$ using the deflation approach employed by Lan et al. (2016). Lan et al. (2016) discuss the approach in detail in their Appendix A.

2.5 Results

2.5.1 Time trends of CO_2 emissions

Figure 2.2 shows the time trend of our estimated consumption-based emissions compared with production-based emissions. We find that between 1990 and 2010, consumption-based emissions increased by 175%, from 98 to 271 teragrams. The growth rate was lower than the production-based emissions, which increased by 204% from 110 to 334 teragrams. Each year, the production-based emissions exceeded the consumption-based emissions by 23.3% on average. A substantial fall in imports during the Asian financial crisis caused the gap between production-based and consumption-based emissions to be largest in 1998—production-based emissions were 40% higher than consumption-based emissions. The fact that the production-based emissions had constantly surpassed the consumption-based emissions suggests that Thailand had always been a net carbon exporter—carbon embodied in exports is larger than carbon embodied in imports. Peters and Hertwich (2008b) show that in 2004, the volume of Thailand's net carbon export was among the world's top ten.

When the production-based emissions are decomposed into domestic emissions and exported emissions, and the consumption-based emissions are decomposed into domestic emissions and imported emissions, we find that almost half (47.3%) of the increase in production-based emissions over 1990–2010 came from exports, while imports accounted for around one third (31.2%) of the increase in consumption-based emissions, as shown in Figure 2.3. Time trends of domestic, exported, and imported emissions are presented in Figure 4. Our results also suggest that, on average, from 1990 to 2010, 46.0% of total CO_2 produced in Thailand each year were exported and 27.4% of total CO_2 consumed in Thailand were imported. The percentage of exported CO_2 is higher than the share of emissions embodied in international trade globally which was estimated to be between 20–33% (Davis and Caldeira, 2010; Peters et al., 2011; Peters and Hertwich, 2008a; Xu and Dietzenbacher, 2014).

Exported emissions of Thailand are also higher proportionally than that of large exporting countries such as China—24.4% in 2001 (Peters and Hertwich, 2008a), 22.5% in 2004 (Davis and Caldeira, 2010), and 33.2% in 2005 (Weber et al., 2008)—and India—13.1% in 2001 (Peters and Hertwich, 2008a) and 18.2% in 2003 (Goldar et al., 2011). Our estimates of the percentage of emissions embodied in trade for Thailand are close to the results in Peters and Hertwich (2008b). They estimated that, for the year 2001, 41.8% of production-based emissions are embodied in exports and 28.1% of consumption-based emissions are embodied in imports. Our results for the same year are 44.9% and 23.5%, respectively.

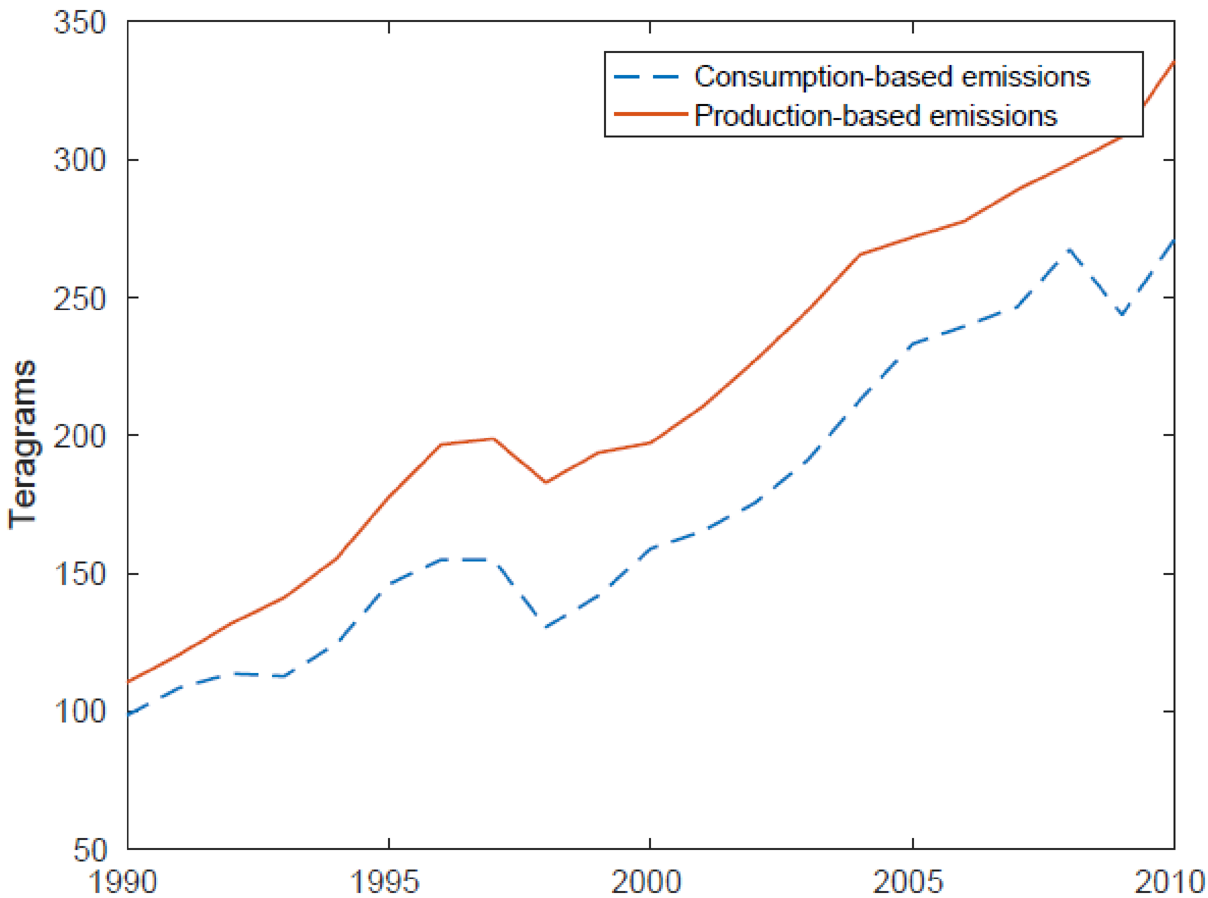

Figure 2.2 Time trends of Thailand's production-based and consumption-based CO_2 emissions 1990–2010

Figure 2.4 shows that, from 1990 until before the Asian financial crisis, imported emissions started lower and grew more slowly than exported and domestic emissions. This is despite the fact that Thailand had experienced a trade deficit throughout that period (World Bank, 2018). Also, Thailand's top imported goods were highly carbon-intensive, e.g., machinery, chemicals, crude oil, and iron and steel (Ministry of Commerce, 2018). The low imported emissions relative to the exported emissions can be explained by the fact that the carbon-intensive imported goods were mostly intermediate products. They were imported mainly for producing final goods which were subsequently exported. Imported final products, on the other hand, were far less carbon-intensive than exported final products. Examples of Thailand's major exports with high import content before the Asian financial are computers and parts, integrated circuits, plastic products, and electrical appliances.

The sharp depreciation of the Thai currency brought by the crisis facilitated export recovery and led to an adjustment of trade balance (Disyatat et al., 2005). Although the currency subsequently recovered, it has constantly remained well below pre-1997 levels. After the crisis, Thailand's trade balance shifted from a large deficit to a surplus most of the time. Our results also show that, in the post-crisis period, the difference between exported and imported emissions is larger than the pre-crisis phase. The gap got wider again when imported emissions declined significantly during the global financial crisis, while exported emissions decreased very slightly.

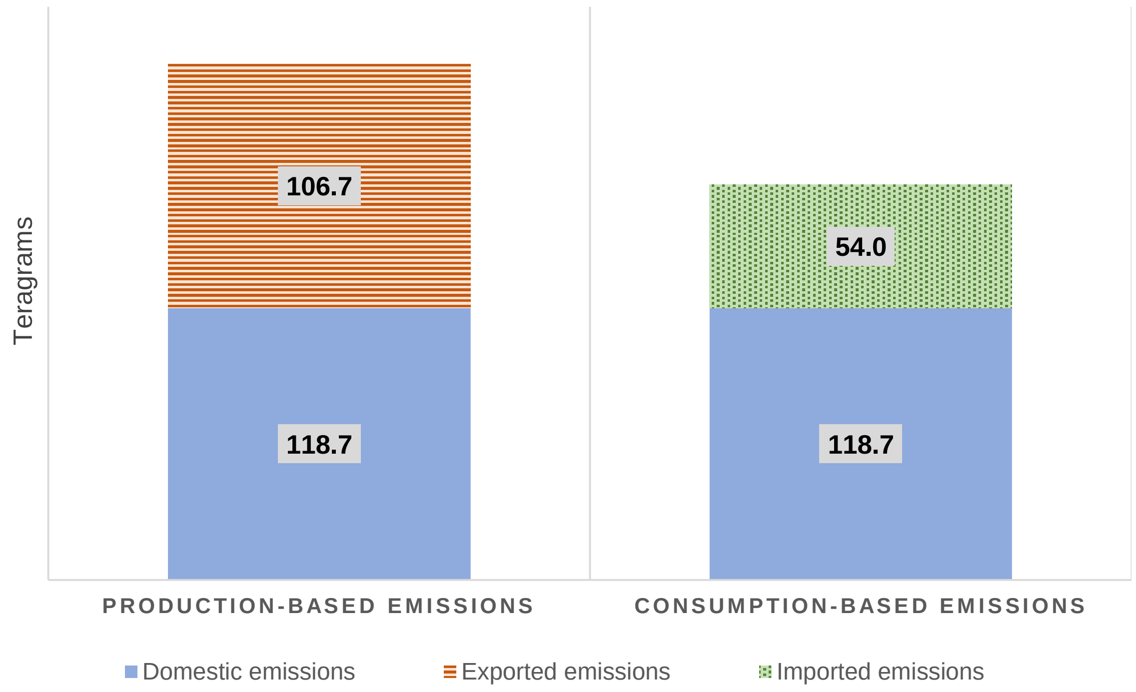

Figure 2.3 Spatial decomposition of change in production-based and consumption-based emissions 1990–2010

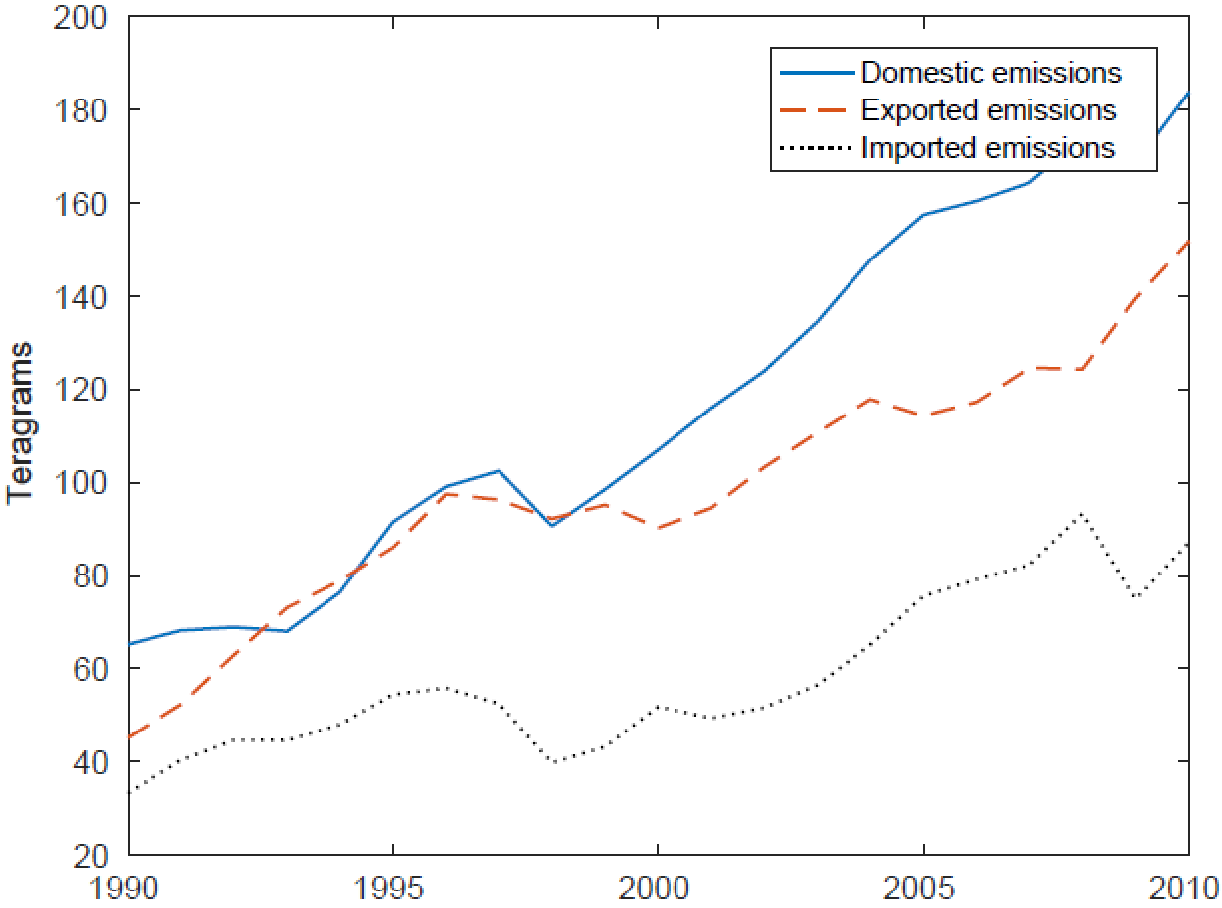

Figure 2.4 Time trends of domestic, exported, and imported carbon emissions 1990–2010

2.5.2 SDA results

The upper panel of Table 2.1 shows the SDA estimates for production-based and consumption-based emissions over 1990–2010. The results for exported, domestic, and imported emissions are presented in lower panel of the table. The results in the upper panel suggest that over the entire period, a rise in both consumption-based and production-based emissions in Thailand was driven mainly by two of the demand-side factors: the affluence effect and population effect. The affluence effect was the most important accelerating factor. This effect contributed to similar changes in production-based and consumption-based CO_2 emissions: 313.1 and 302.1 teragrams, or 139% and 175% of the net changes in emissions. The contribution of the population effect was much lower: 47.2 teragrams for production-based emissions and 42.1 teragrams for consumption-based emissions. Other demand-side factors had relatively trivial effects. On the other hand, two of the supply-side factors—the energy intensity effect and production recipe effect—helped slow down the increase in emissions. Between these two effects, the energy intensity effect played much more important role by contributing to a deceleration of 126.1 and 159.6 teragrams of production-based and consumption-based emissions, or 56% and 92% of the net changes. The results suggest that the key reason making production-based emissions to grow more rapidly than consumption-based emissions is that the energy intensity effect had smaller impact on production-based emissions. The energy intensity effect could cancel only 40% of the increase in production-based emissions caused by the affluence effect. In the case of the consumption-based emissions, the number is 53%. Overall, our findings are consistent with the SDA results for global emissions estimated by Arto & Dietzenbacher (2014), Malik et al. (2016), and Jiang and Guan (2017). They find that the affluence effect surpassed the impact from technological improvement in driving global emissions and emissions from major economies to grow.

Table 2.1 Structural decomposition of production-based and consumption-based CO_2 emissions from 1990 to 2010 (teragrams)

	Net changes	**dc**	**de**	**dL**	**du**	**dv**	**dy**	**dP**
Production-based emissions	225.4	1.8	–126.1	–29.5	13.4	5.5	313.1	47.2
	(100.0%)	(0.8%)	(–55.9%)	(-13.1%)	(5.9%)	(2.4%)	(138.9%)	(21.0%)
Consumption-based emissions	172.6	–0.3	–159.6	–16.5	4.3	0.6	302.1	42.1
	(100.0%)	(–0.2%)	(–92.5%)	(–9.6%)	(2.5%)	(0.4%)	(175.0%)	(24.4%)
Exported emissions	106.7	2.0	–55.3	–0.6	12.0	0.2	129.5	19.0
	(100%)	(1.8%)	(–51.8%)	(-0.6%)	(11.2%)	(0.2%)	(121.3%)	(17.8%)
Domestic emissions	118.7	2.1	–63.0	–28.2	1.6	1.5	181.8	22.8
	(100%)	(1.7%)	(–53.0%)	(–23.7%)	(1.4%)	(1.3%)	(153.2%)	(19.2%)
Imported emissions	54.0	–0.6	–64.4	13.2	2.9	-0.8	92.0	11.7
	(100%)	(–1.1%)	(–119.2%)	(24.4%)	(5.4%)	(-1.4%)	(170.4%)	(21.6%)

Note: **dc** denotes fuel mix effect, **de** denotes energy intensity effect, **dL** denotes production recipe effect, **du** denotes final demand structure effect, **dv** denotes final demand destination effect, **dy** denotes affluence effect, and **dP** denotes population effects.

The lower panel of Table 2.1 shows similar pattern of the SDA results for exported, domestic, and imported emissions: the affluence effect was the strongest accelerating effect while the energy intensity effect was the most important retarding effect. The results reveal that imported emissions grew least rapidly because it had the smallest affluence effect but the greatest energy intensity effect. The fact that the affluence effect was stronger in domestic emissions than in exported emissions suggests that growth in domestic final consumption per capita was still more powerful in driving production-based emissions than growth in final consumption per capita outside Thailand. The results further reveal that the size of energy intensity effect is smaller in production-based emissions than in consumption-based emissions likely because the production of exported final products exhibited less energy efficiency improvement than the production of products consumed in the country (imported and domestically produced). There was no significant difference between the energy intensity effect in domestic and imported emissions.

Figure 2.5 gives a graphic representation of SDA results in five-year sub-periods. The figure suggests that energy intensity in Thailand improved in most of the sub-periods except for the 1995–2000 sub-period, which covers the Asian financial crisis. In this context, the positive energy intensity effect during 1995–2000 does not necessary indicate that Thai producers became less efficient in their energy use. An increase in energy intensity, on the other hand, might be largely explained by the depreciation of Thai baht, brought by the financial crisis. Because the baht's depreciation reduces the value of output produced from Thailand when translated into US dollars, energy intensity calculated from output in terms of US dollars would decline even if energy use remained unchanged. Between 1995 and 2000, the Thai baht depreciated by more than 60% (World Bank, 2018) while aggregate energy consumption increased by 14% (IEA, 2018).[14] The decomposition of traded and non-traded emissions shown in the lower panel of Figure 2.5 points out that in this sub-period imported final products, on the other hand, exhibit an improvement in energy intensity.

Between 1990 and 2010, the Thai government has implemented several measures aiming to enhance energy efficiency. These policy measures might have helped Thailand to reduce its energy intensity which in turn slowed down an increase in domestic and exported emissions. One of the key energy measures implemented in Thailand is the Energy Conservation Promotion Fund (ENCON Fund), which was established in 1992. The fund was

[14] Although it is not ideal that exchange rate fluctuations which is not a part the real economy can affect the results, it is inevitable in the analysis that requires a common currency. Also, the Thai baht exchange rate did not change as substantial in other sub-periods.

sourced from a small levy on all petroleum sold in the country. It provides financial support to government and non-government organizations for the projects designed to increase efficiency in energy use such as machinery replacement, and installation of energy management systems, etc. In addition, A few years after the ENCON Fund was established, buildings and factories consuming greater than 1,000 kilowatt of electricity annually have been required to comply with certain energy standards and submit energy conservation targets and plans.[15] Asia-Pacific Economic Cooperation (2010) and Jue et al. (2012) discuss Thailand's energy efficiency policy in detail.

However, the results suggest that the impact of the energy intensity effect in production-based emissions slowed down during 2005–2010. In particular, for exported emissions, the energy intensity effect declined considerably from 2000–2005 while there was a significant increase in the affluence effect. Altogether, the energy intensity effect in exported and domestic emissions could nullify only one third of the impact of the affluence effect over 2005–2010. This might suggest that the energy policy was not as effective as it used to be during 2000–2005. Meanwhile, we see an increase in the energy intensity effect in imported emissions. It is also possible that the retarding energy intensity effect of all emissions types was escalated after the year 2000 due to a rapid increase in world oil prices (U.S. Energy Information Administration, 2018), which induced energy conservation.[16]

Following the energy intensity effect, the second most important retarding effect is the production recipe effect. However, its size of impact was far less than the energy intensity. As shown in Table 2.1, over 1990–2010, the production recipe effect reduced production-based emissions by 29.5 teragrams and reduced consumption-based emissions by 16.5 teragrams, or 13.1% and 9.6% of the net changes. The production recipe effect of both production-based and consumption-based emissions reduced emissions in all sub-periods except for 2000–2005. Generally, the retarding production recipe effect can be explained by the substitutions of intermediate inputs towards less carbon-intensive inputs. In many cases, it

[15] The energy efficiency regulations for designated buildings have been effective since 1995 while those for designated factories have been effective since 1997.

[16] Thailand has certain fuel price controls that could result in different movements between domestic fuel prices and international crude oil prices. However, domestic prices of many petroleum products often correlate closely with international crude oil prices.

is a result of a decrease in the share of inputs from carbon-intensive industries, such as electricity or transport, in the input structure (Wood and Lenzen, 2009).

During 2000–2005, the production recipe effect increased exported emissions by 28.5 teragrams. The impact is significantly stronger in exported emissions than in domestic and imported emissions. This might be because after Thailand lost its competitive advantage of abundant labor and low wages that it had in the 1990s, the dominant manufacturing exports shifted from labor intensive products, e.g., food and textile, to capital intensive products, e.g., motor vehicle and electronics, in the 2000s (Piya, 2014). The expansion of production scale of capital intensive industries might involve large investments in machinery and equipment, which caused the input structure to be more carbon-intensive. These changes in export structure is consistent to the fact that the final demand composition during the same period had notably accelerating impact for exported emissions, which suggests that exports basket changed towards more carbon-intensive products.

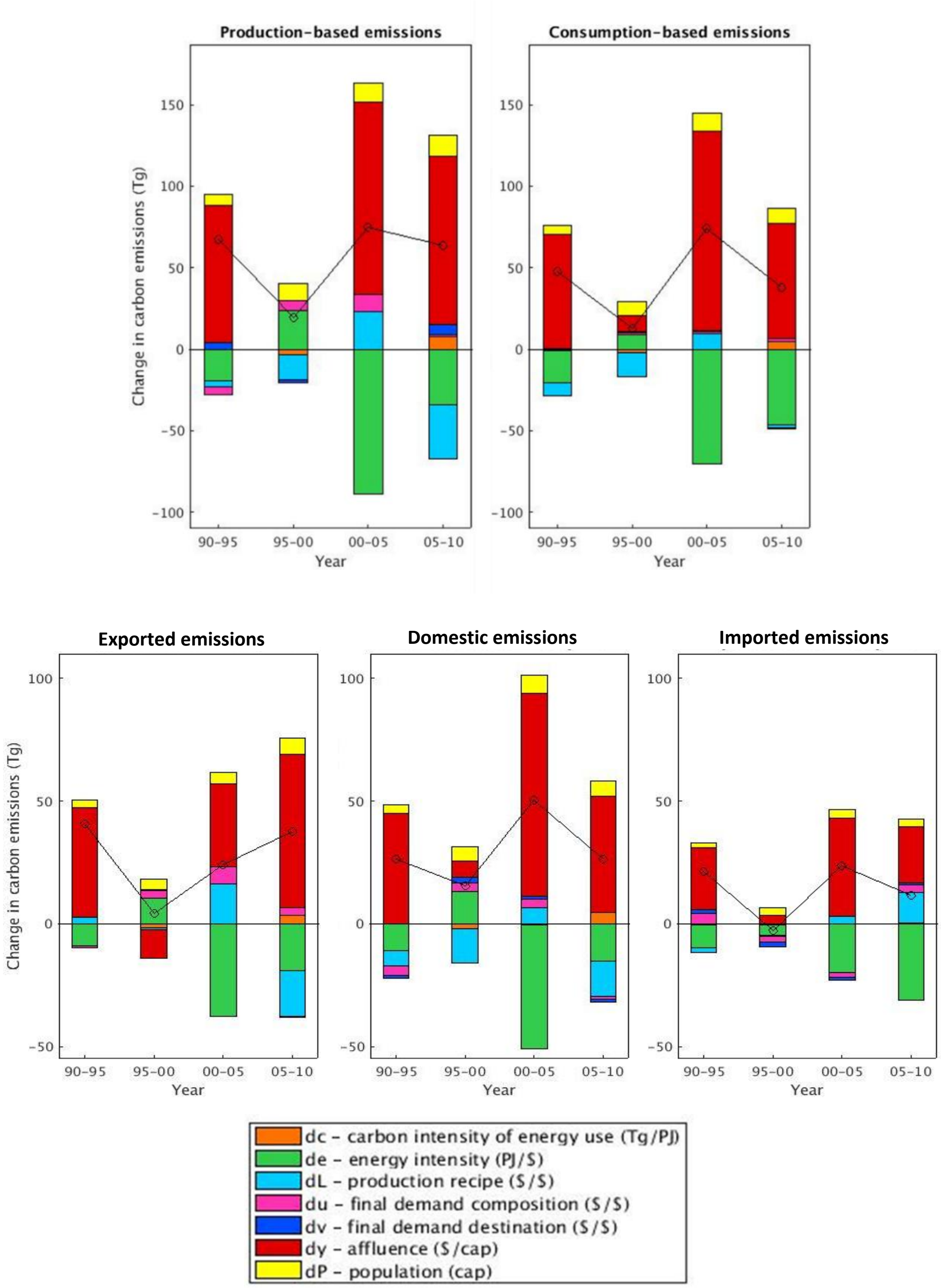

Figure 2.5 Structural decomposition of production-based and consumption-based CO_2 emissions, and emissions by sources 1990–2010. Note: The line graphs represent the net change in total CO_2 emissions in units of teragram (Tg) in five-year intervals. The bar graphs show structural decomposition of the change in total emissions. The energy data are in petajoules (Pj).

In addition, our results in respect of the production recipe effect could showcase how changes in trade structure affected emissions through input substitutions. Between 2005 and 2010, the production recipe effects reduced exported and domestic emissions but increased imported emissions. This might be because that Thailand turned to import goods (for intermediate or final use) which are associated with carbon-intensive intermediate inputs instead of producing them domestically. That is, Thailand might start to outsource some of its emissions to trading partners via input substitution. Malik and Lan (2016) find similar evolution for developed countries over 1990–2010.

The fuel mix effect played a relatively small role compared to other supply-side factors. The overall impact was less than 1% for both production-based and consumption-based emissions. Over the entire study period, the fuel mix effect exhibited fairly similar pattern for all types of emissions. Looking at Thailand's energy use structure, from 1990 to 2005, the share of biomass and biofuels declined continually from 35% to 17% while domestically produced natural gas became the dominant fuel for power generation. The share of natural gas in total energy supply increased from 12% in 1990 to 26% in 2005 (IEA, 2018). The results show that the substitution of biomass with natural gas in the energy profile before 2005 resulted in a retarding fuel mix effect. The contribution, however, was relatively limited because natural gas is not substantially less carbon- intensive than biomass.

Between 2005 and 2010, the energy structure in Thailand has not changed significantly. There was only a small decline in the share of oil and a small increase in the share coal as well as biomass and biofuels whereas the share of natural has remained quite stable (IEA, 2018). An increase in the use of biomass and biofuels was likely due to the promotion of small-scale biomass power plants and the use of biofuels in transport (Kumar et al., 2013). The small-scale substitution towards coal and biomass and biofuels can explain the fact that the fuel mix effect increased emissions slightly.

Considering demand-side factors, as mentioned earlier, the population effect was secondary to the affluence effect in driving up production-based and consumption-based emissions. Figure 2.5 shows that the population effect contributed to an increase in emissions in all sub-periods. Also, the size of the effect did not change very much between sub-periods.

Following the population effect, the final demand composition caused production-based and consumption-based emissions to increase by 5.9% and 2.5% over 1990–2010. The accelerating impact of final demand composition suggests a transition of consumer preferences towards consumption bundles that are more carbon-intensive. The increase of per capita income of the Thai consumers led to a smaller share of spending to basic needs. Statistics show that the Thai consumers spent less, proportionally, on food and clothing but more on vehicles and appliances (Office of the National Economic and Social Development Board, 2018a). The SDA estimates of traded and non-traded emissions, however, show that the final demand composition effect of exports was significantly more pronounced than that of domestically consumed goods. Over the entire period, the final demand composition effect contributed to 11.2% of an increase in exported emissions, compared to 1.4% and 5.4% for domestic and imported emissions. The final demand composition effect in exported emissions was strongest during 2000–2005. Finally, the final demand destination exerted very low influence, especially on consumption-based emissions. This suggest that changes in the consumption-vs.-investment balance and the composition of final consumers—private vs. public—do not affect emissions significantly.

2.5.3 Policy implications

1) Thailand's national climate policy

As mentioned in its Intended Nationally Determined Contribution (INDC), by the year 2030, Thailand aims to reduce its greenhouse gas emissions by 20% from the projected business-as-usual (BAU) level of 555 million tonnes of carbon dioxide equivalent ($MtCO_2e$) (United Nations Framework Convention on Climate Change, 2016). This means that Thailand's greenhouse gas emissions in 2030 should not exceed 444 $MtCO_2e$. However, similar to the energy-related CO_2 emissions, Thailand's greenhouse gas emissions is on the rising trend and already reached 440 $MtCO_2e$ in 2012 (World Bank, 2018). If there is no revolution in energy use in the near future, it is unlikely that Thailand will achieve the emissions reduction target.

Given that more than half of total greenhouse gases in Thailand are energy-related CO_2, it is important for the government to focus on reducing energy-related CO_2. The SDA results suggest that, if past trends continue, the overall retarding effects need to at least double to overcome the accelerating impacts from the demand side. Although energy efficiency gains and production recipe adjustments were helpful, these effects are difficult to be scaled up rapidly. Thailand has planned to continue implementing policy measures to reduce energy intensity. However, it is expected that, in 2036, energy intensity will reduce by only 30% comparted to 2010 (The Energy Policy and Planning Office, 2015).

Therefore, a possible approach to reverse the emission trend is to accelerate an uptake of zero-emission renewable energy to amplify the retarding fuel mix effect. Although Thailand has set a target to increase the share of renewable energy in final energy consumption to 30% in 2036, the target also covers biomass and biofuels, which are non-zero emissions renewable energy (Department of Renewable Energy Development and Energy Efficiency, 2015). In 2015, biomass and biofuels already accounted for around 19% of total energy use in Thailand (IEA, 2018). In contrast, the share of zero-emission energy sources in Thailand in 2015 is still very inconsiderable—less than 1%. However, Thailand has a high potential for solar energy because around 50% of its area is exposed to concentrated sunlight all year round (Sitdhiwej, 2016). Also, the unit cost of solar PV has fallen dramatically in recent years (IEA, 2016a). As a result, Thailand possesses a tremendous opportunity to hasten the solar power revolution and achieve a decline in CO_2 emissions.

2) Global climate policy

As shown in Section 4.1, a great portion of CO_2 emissions that took place in Thailand came from the production of exports, and this part of emissions was driven to increase largely by the growth of final demand in other countries. Table 2.2 compares emissions embodied in international trade for Thailand with the estimates for selected countries from Peters and Hertwich (2008a). The numbers are expressed in terms of percentage of the production-based emissions. For Thailand, emissions embodied in exports exceeded emissions embodied in imports by around 19%. On the contrary, many developed countries are found to have emissions embodied in imports significantly greater than emissions embodied in exports. As shown by Peters and Hertwich (2008a), Belgium, Sweden, and Netherlands were countries with biggest emissions deficits. The levels of deficits range from 19% to 44%. Most developing countries such as China and India are found to have emissions surpluses, similar to Thailand.

Table 2.2 Comparison of emissions embodied in international trade between Thailand and other countries (% of production-based emission)

	Exported emissions (1)	**Imported emissions** (2)	**Emissions balance** (1) – (2)
Results from this study: average from 1990 to 2010			
Thailand	46.0	27.4	18.6
Results from Peters and Hertwich (2008a): for the year 2001			
Belgium	45.5	89.4	–43.9
Sweden	34.1	73.7	–39.7
Netherlands	39.1	58.1	–19.0
China	24.4	6.6	17.8
India	13.1	6.2	6.9

The consumption-based accounting is useful to reveal information of how international trade affects emissions in each countries but, due to its disadvantages, the consumption-based accounting is yet unlikely to replace the mainstream production-based accounting (Peters, 2008; Afionis et al., 2017). However, incorporating consumption-based emissions into the existing production-based NEI could be beneficial. For example, an indicator from the consumption-based accounting may increase emissions mitigation efforts by encouraging developed countries to transfer mitigation technology or invest in projects that reduce emissions in developing countries (Peters, 2008; Wiedmann, 2009). Stern et al., (2012) find that marginal costs of abatements are lower in countries with higher emissions intensity such as China and India, in contrast to EU and USA. This means that it tends to be more cost-effective to reduce the same amount of CO_2 emissions in China and India than in EU and USA.

2.6 Conclusion

This study has provided insights of Thailand's production-based and consumption-based emissions. Our results show that from 1990 to 2010, Thailand was always a net CO_2 exporter although Thailand sometimes experienced a trade deficit. On average, each year production-based emissions surpassed consumption-based emissions by 23%. When emissions are decomposed into traded and non-traded parts, we find that almost half of emissions taking place in Thailand was a result of exports. On the other hand, emissions embodied in imports accounted about one-fifth of Thailand's consumption-based emissions. Our findings confirm that Thailand was one of the world's carbon sinks like other developing countries, e.g., China and India (Peters and Hertwich, 2008a; Malik et al., 2016).

The SDA estimates indicate that although an improvement in production technology played an important role in decelerating emission growth in Thailand, it could only partly offset the strong influence from demand-side factors, especially the affluence (per capita consumption) effect. The most important retarding effect was the increase in energy use efficiency, whereas changes in fuel mix only had a minor impact. Previously, the impact of the fuel mix effect was negligible because the share of zero-emission renewables had been minimal. However, in the near future, it is possible for the fuel mix effect to play an important role if a rapid transition towards zero-emission energy sources takes place in Thailand.

When applying SDA to domestic, exported, and imported emissions, our results show certain interesting findings. First, the energy intensity effect caused a smaller reduction in exported emissions than in domestic and imported emissions. More importantly, over 2005–2010, the retarding impact of the energy intensity effect in exported emissions declined while the impact of the affluence effect increased. Second, over the latter years of the study period, the accelerating impact from changes in the composition of consumer basket was strongest in the case of exported emissions. If this trend continues, exported emissions are likely to grow not only because of the scale effect but also because Thailand's exports are becoming more carbon intensive. Finally, between 2005 and 2010, Thailand started to exhibit a carbon outsourcing activity by substituting imported carbon-intensive intermediate goods for domestic ones to produce final goods that were eventually consumed in Thailand. This exerted an upward pressure on imported emissions and a downward pressure on domestic emissions. However, the scale of this effect was relatively small and it is unlikely to transform Thailand to a net carbon importer in the near future.

Looking at the global picture, a great deal of Thailand's net exported carbon demonstrates a case of how, under the Kyoto Protocol, countries that rely on exports to drive their economies, usually developing countries, must bear the responsibility of emissions produced to serve foreign final demand. In this regard, we see the benefits of adopting consumption-based emissions as a complementary indicator to the existing National Emissions Inventory. Reporting consumption-based emissions could motivate developed countries to provide mitigation assistance via technology transfers or financial supports and could accelerate emission reduction in developing countries where marginal costs of abatement are likely to be lower.

A Appendix

A.1 Sector classification

1. Agriculture
2. Fishing
3. Mining and Quarrying
4. Food & Beverages
5. Textiles and Wearing Apparel
6 Wood and Paper
7. Petroleum, Chemical and Non-Metallic Mineral Products
8. Metal Products
9. Electrical and Machinery
10. Transport Equipment
11. Other Manufacturing
12. Recycling
13. Electricity, Gas, and Water Supply
14. Construction
15. Maintenance and Repair
16. Wholesale Trade
17. Retail Trade
18. Hotels and Restaurants
19. Transport
20. Post and Telecommunications
21. Financial Intermediation and Business Activities
22. Public Administration
23. Education, Health and Other Services
24. Private Households

25. Others
26. Re-export & Re-import

A.2 List of countries

1. Afghanistan
2. Albania
3. Algeria
4. Andorra
5. Angola
6. Antigua
7. Argentina
8. Armenia
9. Aruba
10. Australia
11. Austria
12. Azerbaijan
13. Bahamas
14. Bahrain
15. Bangladesh
16. Barbados
17. Belarus
18. Belgium
19. Belize
20. Benin
21. Bermuda
22. Bhutan
23. Bolivia
24. Bosnia and Herzegovina
25. Botswana
26. Brazil
27. British Virgin Islands
28. Brunei
29. Bulgaria
30. Burkina Faso
31. Burundi
32. Cambodia
33. Cameroon
34. Canada
35. Cape Verde
36. Cayman Islands
37. Central African Republic

38. Chad
39. Chile
40. China
41. Colombia
42. Congo
43. Costa Rica
44. Croatia
45. Cuba
46. Cyprus
47. Czech Republic
48. Cote d'Ivoire
49. North Korea
50. DR Congo
51. Denmark
52. Djibouti
53. Dominican Republic
54. Ecuador
55. Egypt
56. El Salvador
57. Eritrea
58. Estonia
59. Ethiopia
60. Fiji
61. Finland
62. France
63. French Polynesia
64. Gabon
65. Gambia
66. Georgia
67. Germany
68. Ghana
69. Greece
70. Greenland
71. Guatemala
72. Guinea
73. Guyana
74. Haiti
75. Honduras
76. Hong Kong
77. Hungary
78. Iceland
79. India
80. Indonesia

81. Iran
82. Iraq
83. Ireland
84. Israel
85. Italy
86. Jamaica
87. Japan
88. Jordan
89. Kazakhstan
90. Kenya
91. Kuwait
92. Kyrgyzstan
93. Laos
94. Latvia
95. Lebanon
96. Lesotho
97. Liberia
98. Libya
99. Liechtenstein
100. Lithuania
101. Luxembourg
102. Macao SAR
103. Madagascar
104. Malawi
105. Malaysia
106. Maldives
107. Mali
108. Malta
109. Mauritania
110. Mauritius
111. Mexico
112. Monaco
113. Mongolia
114. Montenegro
115. Morocco
116. Mozambique
117. Myanmar
118. Namibia
119. Nepal
120. Netherlands
121. Netherlands Antilles
122. New Caledonia
123. New Zealand

124. Nicaragua
125. Niger
126. Nigeria
127. Norway
128. Gaza Strip
129. Oman
130. Pakistan
131. Panama
132. Papua New Guinea
133. Paraguay
134. Peru
135. Philippines
136. Poland
137. Portugal
138. Qatar
139. South Korea
140. Moldova
141. Romania
142. Russia
143. Rwanda
144. Samoa
145. San Marino
146. Sao Tome and Principe
147. Saudi Arabia
148. Senegal
149. Serbia
150. Seychelles
151. Sierra Leone
152. Singapore
153. Slovakia
154. Slovenia
155. Somalia
156. South Africa

157 Spain
158 Sri Lanka
159 Suriname
160 Swaziland
161 Sweden
162 Switzerland
163 Syria
164 Taiwan
165 Tajikistan
166 Thailand

167	TFYR Macedonia
168	Togo
169	Trinidad and Tobago
170	Tunisia
171	Turkey
172	Turkmenistan
173	Uganda
174	Ukraine
175	UAE
176	UK
177	Tanzania
178	USA
179	Uruguay
180	Uzbekistan
181	Vanuatu
182	Venezuela
183	Viet Nam
184	Yemen
185	Zambia
186	Zimbabwe

A.3 Concordance matrix for matching the IEA’s sectors with Eora’s sectors

		EORA's sectors																								
		Agriculture	Fishing	Mining and Quarrying	Food & Beverages	Textiles and Wearing Apparel	Wood and Paper	Petroleum, Chemical and Non-Metallic Mineral Products	Metal Products	Electrical and Machinery	Transport Equipment	Other Manufacturing	Recycling	Electricity, Gas, and Water Supply	Construction	Maintenance and Repair	Wholesale Trade	Retail Trade	Hotels and Restaurants	Transport	Post and Telecommunications	Financial Intermediation and Business Activities	Public Administration	Education, Health and Other Services	Private Households	Others
IEA's sectors	Iron and steel	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Chemical and petrochemical	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Non-ferrous metals	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Non-metallic minerals	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Transport equipment	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Machinery	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Mining and quarrying	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Food and tobacco	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Paper, pulp, and printing	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Wood and wood products	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Construction	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
	Textile and leather	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Non specified (industry)	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Transport	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
	Commercial and public services	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
	Agriculture/forestry	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Fishing	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Electricity	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
	Residential	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
	Other	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Chapter 3

GDP elasticity of electricity demand in Thailand: Constant or varying?

3.1 Chapter overview

In this chapter, I investigate the relationship between electricity consumption and per capita gross domestic product (GDP) in Thailand using provincial data from 2006 to 2016. I seek to find whether the effect of GDP on electricity demand varies with the levels of GDP. Various econometric techniques are applied to estimate GDP elasticity of electricity demand in the short run, in five- and ten-year periods, and in the long run. My estimates suggest that GDP elasticity electricity demand is lower at higher GDP levels. This is similar for residential, non-residential, and total electricity demand. The findings imply that a declining electricity-GDP elasticity will provide a more precise electricity demand forecast than a constant elasticity.

3.2 Introduction

Economic growth, measured using GDP, is usually an important factor used to project national or regional electricity demand (see, for example, von Hirschhausen and Andres (2000), Liao et al. (2017), Steinbuks et al., (2017), and Vu et al., (2017)). For Thailand, the recent national electricity forecast is presented in the power development plan 2015–2036 (PDP 2015; the Energy Policy and Planning Office (2015)). As discussed in the plan, the electricity forecast is based upon the long-term projection of GDP growth, and the electricity forecast is employed to plan for future investments in the power system.

To produce a reliable electricity demand forecast, not only is information about the magnitude of electricity-GDP elasticity essential, but knowing whether the elasticity changes or remain constant with respect to GDP is also important. Most of the previous studies testing the varying GDP elasticity utilise international samples and investigate energy demand in general rather than examine electricity demand in particular. Yet, the results are fairly inconclusive.

Studies examining commercial energy demand tend to find that the income elasticity of commercial energy demand likely declines with respect to income, e.g., Galli (1998), Judson et al. (1999), and Medlock and Soligo (2001). Examples of the possible reasons for the declining income elasticity are economic structural change and efficiency improvement (Galli, 1998). As countries move towards a post-industrial phase, production will shift from manufacturing to services, which are less energy intensive. Furthermore, as income rises, advanced energy technologies will become more affordable.

On the other hand, studies that include traditional biomass in their datasets are inclined to find that the energy-income elasticity actually increases as countries become richer (van Benthem and Romani, 2009; Csereklyei and Stern, 2015; Burke and Csereklyei, 2016). However, van Benthem and Romani (2009) show that increasing income elasticity is mainly found in the lower-income band of the sample. The evidence of a declining income elasticity is found at the per capita income levels above 5,000 US dollar at purchasing power parity (in constant 2000 US dollar). Furthermore, Burke and Csereklyei (2016) show that when traditional biomass is excluded, they find no strong evidence that the energy-income elasticity increases with income.

Very few studies have attempted to investigate the change in GDP elasticity of particular types of energy sources such as electricity. The electricity-GDP relationship may not be a replicate of the energy-GDP relationship. Electricity is considered a top-tier energy source. As their incomes increase, households switch from traditional biomass to transition fuels such as kerosene and coal, and then to modern energy such as liquefied petroleum gas, natural gas and electricity (Heltberg, 2004; Burke, 2013). In addition, adoption of advanced production technology likely increases the electricity share in the energy mix of industrial firms (Doms and Dunne, 1995; Jung and Lee, 2014). Therefore, an increase in income tends to have a greater impact on electricity demand than on aggregate energy consumption. Burke and Csereklyei (2016) find that the GDP elasticity of electricity demand is larger than that of aggregate energy demand. They also test whether or not electricity-GDP changes with GDP but do not find evidence for this.

This paper examines the relationship between electricity demand and GDP by using Thailand as a case study. The research has the key objectives of estimating electricity-GDP elasticity and testing whether the elasticity varies with the levels of GDP per capita. It aims to provide useful implications for electricity demand forecasting. GDP, rather than other income data (e.g., household income), is used because GDP is the basis for projecting electricity demand and framing future power investment in Thailand's power development plan. Data for 74 provinces over the period 2006–2016 are employed in the study.[17] The findings suggest that the GDP elasticity of electricity demand in Thailand declines as GDP per capita increases. Similar phenomena are observed for residential, non-residential, and total electricity consumption.

To my knowledge, this study is the first to test the change in the income effects on aggregate electricity consumption using an intra-country sample. An intra-country sample, in contrast to an international sample, can avoid heterogeneity among different countries. Yin et al. (2016) test the varying electricity-income elasticity in China using provincial data, but study only residential electricity demand. They find that income elasticities of residential electricity use decrease as income increases. Furthermore, this is the first paper investigating electricity demand in Thailand by employing provincial data. Other studies such as the study executed by Kandananond et al. (2011) uses national time series data. Furthermore, in this study, I present the results that control for development-related factors in addition to GDP such as urbanization, structural change, and electricity access. These variables are rarely included in existing studies of electricity demand.

The rest of the chapter is structured as follows. Section 3.3 provides the background information about electricity demand in Thailand. Section 3.4 discusses methodology. Section 3.5 describes the data sources. Section 3.6 presents the estimation results. Section 3.7 concludes and discusses policy implications.

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[17] In the dataset, I combine Bangkok, Nonthaburi, and Samutprakan into one province because the Metropolitan Electricity Authority—the retail electricity provider in these three provinces—does not provide some of the data at the province level. I also combine Nongkhai and Bungkan into one province. Bungkan was separated from Nongkhai in 2011. For the consistency of the data, I treat these two provinces as one province.

3.3 Electricity consumption in Thailand

Electricity accounted for around 15% of total final energy consumption in Thailand in 2015 (in joules; IEA, 2018); other key sources for final energy consumption are oil and biomass. In 2016, 100% of the population of Thailand has access to electricity. The number increased rapidly from 76% in 1990 (World Bank, 2018). In 2006, residential electricity consumption contributed around 22% of total electricity consumption. The share increased slightly to 25% in 2016. Figure 3.1 compares annual residential and non-residential electricity consumption in Thailand from 2006 to 2016 in units of terawatt-hours (TWh).

The Electricity Generating Authority of Thailand (EGAT), a state-owned enterprise, is the largest electricity producer in Thailand, responsible for 38% of total electricity production in 2015 (Sirasoontorn and Koomsup, 2017). EGAT also partially owns the two largest independent power producers, which altogether account for 25% of total power generation. Furthermore, EGAT is the only power transmission operator in Thailand. All electricity producers sell electricity to EGAT under long-term power purchase agreements (DBS Group Research, 2017). Electricity retail distribution is operated by two different state-owned enterprises, the Metropolitan Electricity Authority (MEA) and the Provincial Electricity Authority (PEA), which buy electricity from EGAT.

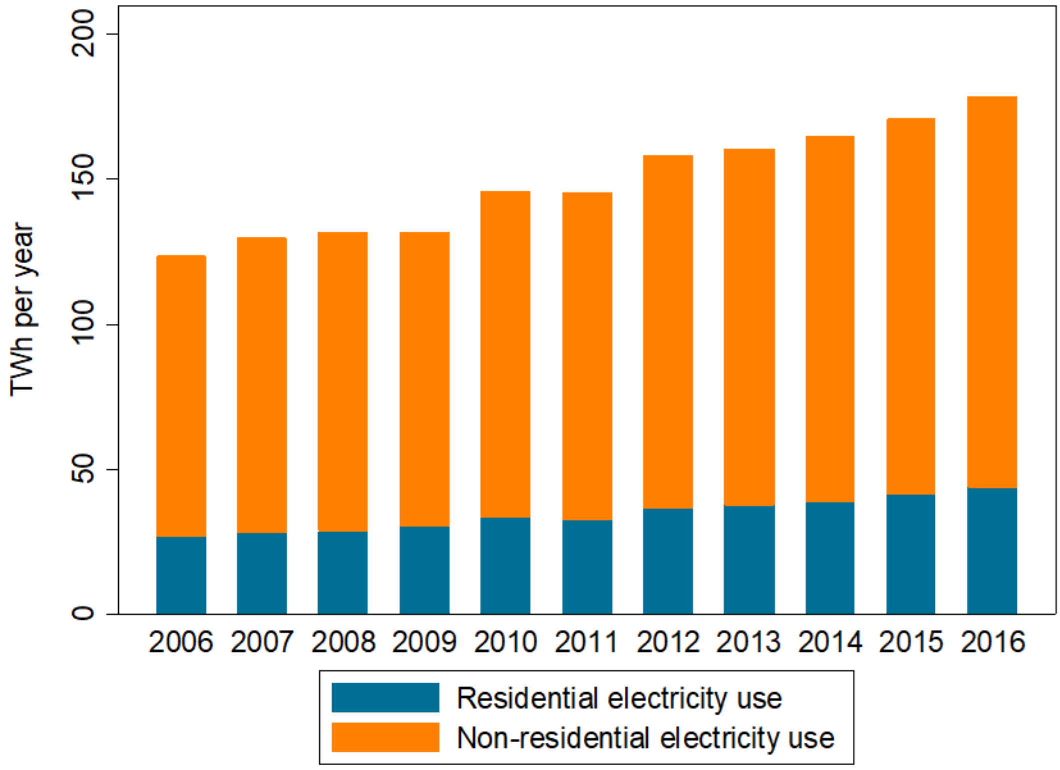

Figure 3.1 Residential and non-residential electricity use in Thailand 2006–2016. Source: The National Statistical Office of Thailand (NSO, 2015; 2017).

Electricity consumption per capita in Thailand increased by 5.4% per annum on average over 1990–2015. The growth rate of electricity consumption is slightly greater than GDP per capita, which increased by an average of 3.4% per annum. Figure 3.2 presents the time series of per capita electricity consumption and per capita GDP. It is shown that electricity consumption correlates highly with GDP. Electricity consumption increased when the economy was growing and declined when there was an economic recession.

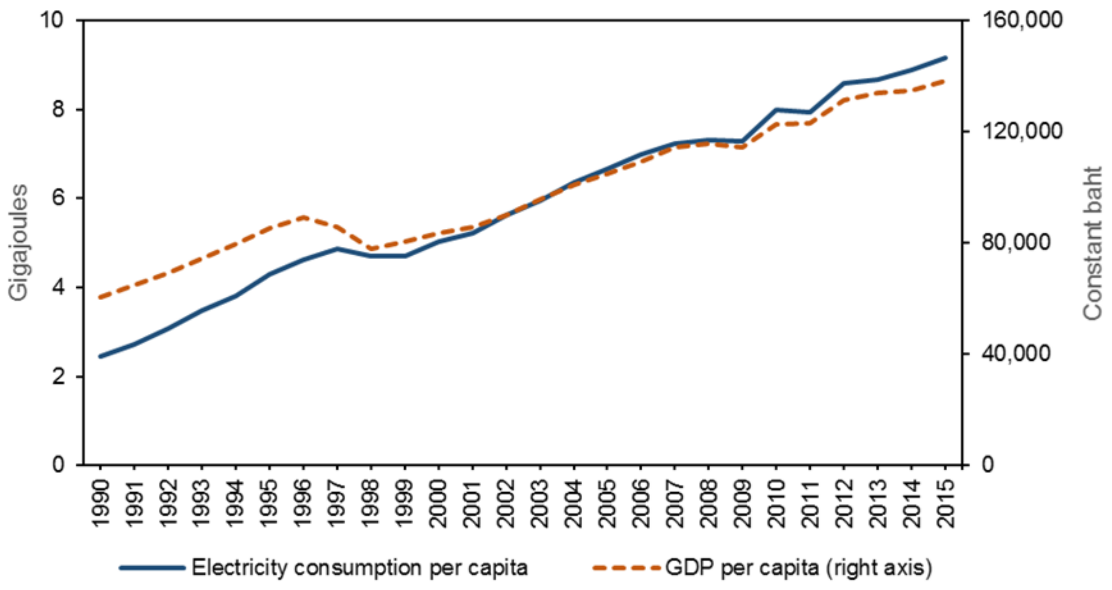

Figure 3.2 Electricity consumption per capita and GDP per capita in Thailand 1990–2015. Sources: Electricity consumption is collected from IEA (2018). GDP per capita is collected from the World Bank (2018).

At the provincial level, there is substantial variation in electricity consumption per capita. In 2016, Maehongson had the lowest provincial electricity consumption per capita of 434 kilowatt-hour (kWh) per year while the number was as high as 14,867 kWh per year in Rayong. Figure 3.3 presents the scatter plot between the log of provincial electricity consumption per capita and the log GDP per capita in 2016. The figure compares residential, non-residential, and total electricity consumption. It is shown that provinces with higher GDP per capita consume more electricity. The slope of the fitted lines represents the GDP elasticity at the corresponding GDP level. A strictly concave pattern shown in the fitted lines for residential, non-residential, and total electricity consumption suggests that GDP elasticity likely decreases as GDP per capita rises.

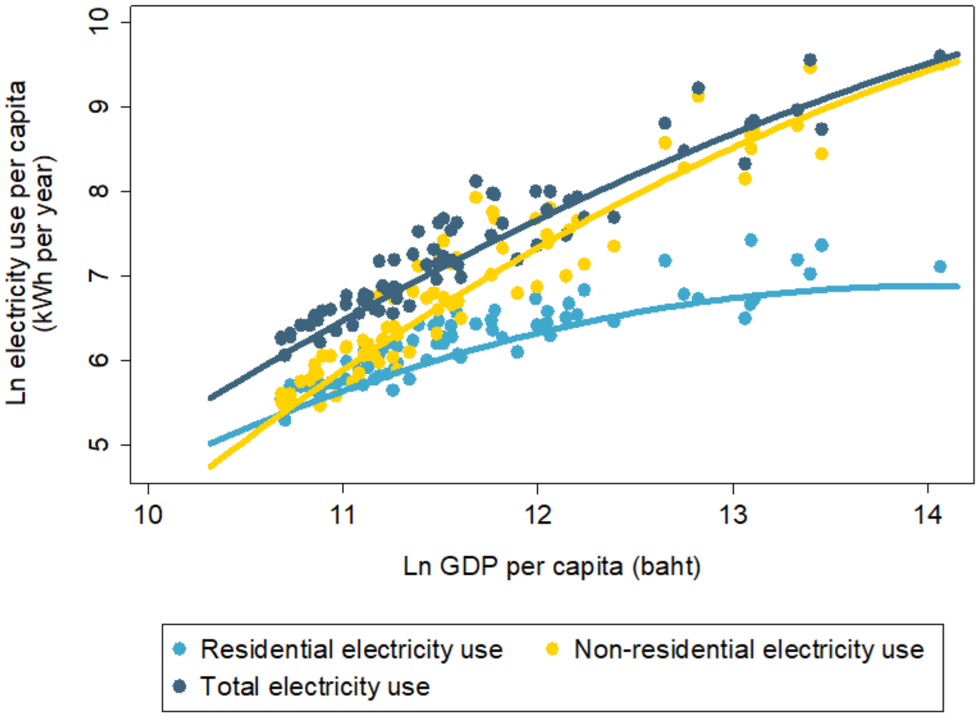

Figure 3.3 Log electricity consumption per capita and log GDP per capita of 74 provinces in 2016. Sources: Electricity use is collected from NSO (2015; 2017). GDP is collected from the Office of the Economic and Social Development Board (NESDB, 2018).

Figure 3.4 shows the business-as-usual (BAU) electricity forecast obtained from Thailand's power development plan 2015–2036 or PDP2015 (The Energy Policy and Planning Office, 2015). The BAU case takes into account potential power demand savings from the energy conservation measures already implemented but not potential savings from the measures planned to be implemented in the future. The implemented energy conservation measures are expected to result in a reduction of 27,282 gigawatt-hours (GWh) in the total demand in 2036.

The PDP's power demand projection is estimated based on the forecasted GDP per capita growth of around 4% per annum on average. The PDP forecasts that electricity consumption per capita in Thailand will grow around 4% per annum over the first five years of the plan and decrease gradually to around 3% in 2036. The grey line represents the implied unconditional electricity-GDP elasticity calculated by comparing the power demand and GDP forecasts from the PDP and adjusted into per capita terms to make them consistent with the discussions in other parts of this study. The elasticity is slightly less than unity, around 0.95, in 2021 and reduces slowly to around 0.85 in 2036. However, the fact that the implied elasticity declines over time tends to be because of the expected energy savings from government measures, rather than from the fact that elasticity is adjusted corresponding to the increasing GDP. Without the effect of energy savings, the implied elasticity would be 1.01 in 2036.

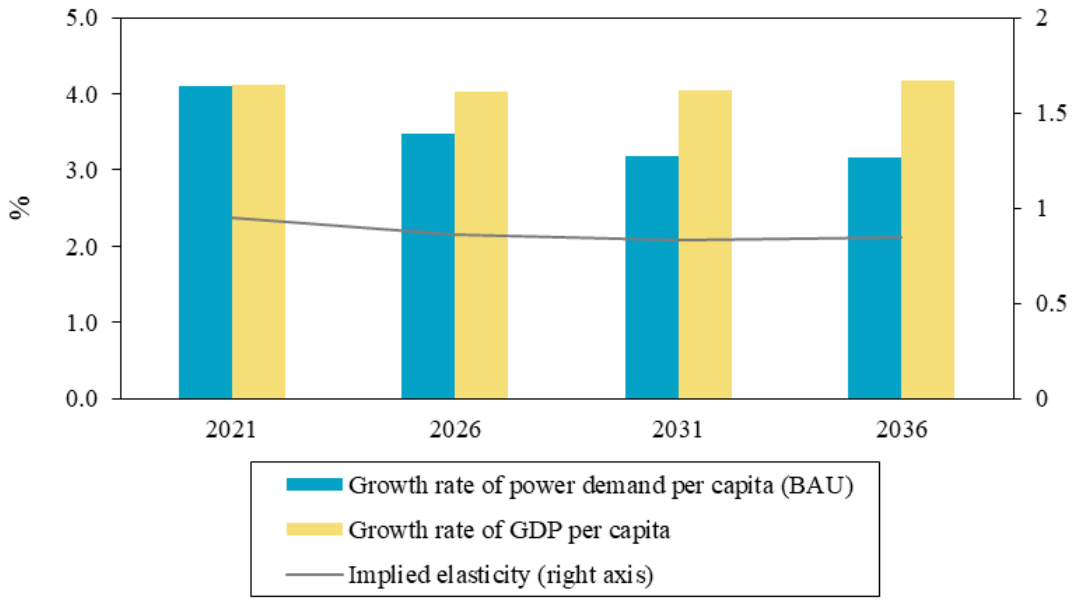

Figure 3.4 Forecast of business-as-usual electricity demand from PDP2015. PDP2015 provides the forecasts of electricity demand (business-as-usual case) and growth rates of GDP levels until 2036. I adjust the forecast into a per-capita term using the population growth projection from NESDB (2018b). The growth rate of power demand forecast is calculated from demand in GWh.

In this study, not only do I find that electricity-GDP elasticity tends to decline as GDP per capita grows over time, my results also show that the elasticity at a point in time is likely different between provinces: smaller elasticity tends to occur in richer provinces. This suggests that, given the same economic growth rate, richer provinces tend to require a smaller proportion of additional electricity supply than provinces with lower GDP levels.[18]

[18] There is no discussion in PDP2015 that the forecast is also executed at the provincial level.

3.4 Econometric models

This study utilizes different estimation methods to obtain coefficients for different time frames. The short-run coefficients are obtained from the within estimator or the fixed-effects model. The within estimator utilizes the time-series dimension of panel data, which demonstrates the year-to-year adjustments of each province due to time-varying factors. It has long been argued that time-series regression tends to give short-run estimates while cross-sectional estimation tends to give long-run effects (for example, Kuh, 1959; Griffin and Gregory, 1976; Baltagi and Griffin, 1984).

Next, I employ the growth rate models to obtain estimates for the 5-year and 10-year responses. The estimation of the growth rate models begins with obtaining 5-year and 10-year growth rates of data in each province. After this, the coefficients are estimated by employing the cross-sectional variation of the growth rates. The growth rate models likely provide longer-run estimates than the fixed-effects model because the models remove short-term variation and give importance to the behavior of the time series in the longer term (Chirinko et al., 2011; Csereklyei and Stern, 2015; Stern et al., 2017). Similar approaches are also used by Chirinko et al. (2011), Jakob et al. (2012), Csereklyei and Stern (2015), Burke and Csereklyei (2016), Ma and Stern (2016), and Stern et al. (2017).

For the long-run effects, the coefficients are estimated using cross-section regression and the between estimator. The between estimator is similar to cross-section regression except that the between estimator uses averages across time of each individual. Pirotte (1999) concludes that the long-run coefficients can be estimated using the between estimator without employing dynamic models, which requires an assumption about the specification of the dynamic process. He shows that when the number of individuals tends to infinity and the time dimension is fixed, the probability limit of the between estimator applied to a static panel model converges to long-run effects. This is even the case where the true model is a dynamic one. Examples of studies using the between estimator to estimate long-run effects include studies executed by Stern (2010), Burke and Nishitateno (2015), Ma and Stern (2016), and Burke and Abayasekara (2018). The following sub-sections present the model specifications for short-run, 5- and 10-year growth rates, and long-run estimation.

3.4.1 Fixed-effects estimation

The fixed-effects model for estimating short-run response has the following specification:

$$\ln E_{i,t} = \alpha_0 + \alpha_1 \ln Y_{i,t} + \alpha_2 (\ln Y_{i,t})^2 + \alpha_3 \pi_i + \boldsymbol{X}'_{i,t} \boldsymbol{\theta} + \varepsilon_{i,t} \tag{3.1}$$

where E is electricity consumption per capita in province *i* at year *t* in kilowatt-hours (kWh), Y is real GDP per capita, π is a set of province fixed effects, $\boldsymbol{X}$ is a vector of control variables, and ε is an error term. The quadratic term of log of real GDP per capita $\left(\ln Y_{i,t}\right)^2$ is included to allow the GDP elasticity to vary with GDP levels. With the term $\left(\ln Y_{i,t}\right)^2$, the GDP elasticity follows $\alpha_1 + 2\alpha_2(\ln Y_{i,t})$. If $\alpha_2 < 0$ and significant, the GDP elasticity declines as GDP per capita grows. The Y level at the turning point is calculated by setting $\alpha_1 + 2\alpha_2(\ln Y_{i,t}) = 0$.

Many studies, such as the ones conducted by Galli (1998), Medlock and Soligo (2001), and van Benthem and Romani (2009), include a squared log of GDP and find that energy-GDP elasticities are likely to decline as GDP increases once GDP passes certain level. If energy use is considered as one type of environmental pressure, the findings of these studies would be in line with the concept of environmental Kuznets curve (EKC) (Stern, 2004, 2017). Some proximate factors that are used to explain the EKC hypothesis might also be the causes of the declining energy-GDP elasticity. For example, changes in economic structure, an increase in production efficiency, and the substitution of energy with other inputs. Luzzati and Orsini, (2009) test the energy-EKC relationship but do not find the evidence to support the hypothesis. However, it is important to note that, similar to many studies focusing on testing the EKC hypothesis, Luzzati and Orsini, (2009) do not seem to include sufficient control variables and their results, therefore, might suffer from omitted variable bias (Stern, 2017)The vector of control variables in Equation (3.1) includes the log of real electricity price index and a set of time dummies for electricity price subsidy, the log of liquid petroleum gas (LPG) price representing the price of electricity substitute, the log of cooling degree days to control for changes in temperature. Warmer temperature is expected to increase electricity demand, especially due to the use of air conditioning (Parkpoom and Harrison, 2008). For residential and total consumption, household size is also included.

I calculate the retail electricity price index using electricity tariff schedules.[19] In Thailand, the same tariff schedule is applied to the entire country. Electricity tariffs for residential users and part of non-residential users increases with quantity of electricity use. On the other hand, most non-residential users, accounting for more than 76% of non-residential electricity use in 2006, are charged flat rates but the rates are higher for high-voltage users. For the residential price, I use a single representative consumption level to calculate the price for all provinces. A single representative consumption level is employed to reduce the effect of an endogeneity issue due to the fact that more electricity consumed results in a higher electricity price. For non-residential consumption, the electricity price is the simple average of prices for all voltage levels. The total electricity price is the weighted average of residential and non-residential prices. The Appendix discusses in detail the structure of electricity prices in Thailand and how I calculate the electricity price index.

The above calculation approach gives the same nominal electricity price index for all provinces. However, the real electricity price index varies between provinces due to the differences in the provincial inflation adjustment. This is similar to the case of LPG price because the data are available only for the capital city and the surrounding areas (i.e., the BMR and Pathumthani). In each province, the inflation adjustment reflects the overall price level in a particular year relative to the price level in the base year.

I use time dummies to control for the electricity price subsidy implemented in Thailand from 2008 to 2016. Over 2008–2016, there were a few revisions of the subsidy conditions. Details are shown in Table A.1 in the Appendix. There are six time dummies I use for the electricity price subsidy: 2008, 2009, 2010–2011, 2012, 2013–2015, and 2016.

[19] Another approach to calculate electricity price is to divide the provincial electricity sales revenue by the quantity of electricity sole. This approach will yield provincial average electricity price. However, I chose not to use this approach due to a data availability issue. The revenue data recorded by the MEA and PEA are the revenue from electricity sold plus electricity subsidy expenses, which MEA and PEA will be compensated by the government. In other words, the recorded revenue data are the revenue as if there was no subsidy. To obtain the true revenue, one must subtract the subsidy expenses from the recorded revenue. Nevertheless, the subsidy expenses data at the provincial level are unavailable for many years. Using the recorded revenue to calculate average electricity price directly would be inappropriate because there were millions of subsidy recipients each year (The International Institute for Sustainable Development, 2013).

The same dummy is applied for 2010–2011 because the subsidy conditions remained unchanged throughout this period, likewise 2013–2015. The subsidy mainly targets small residential electricity users. Only during August 2008 – January 2009 that the subsidy scheme also included tenants of residential property, which are part of non-residential users. However, it is possible that the subsidy scheme after January 2009 still affected non-residential electricity use through a growth in non-electricity household spending, which induces production activities to increase. Therefore, I use the same subsidy time dummies for residential, non-residential, and total electricity use.

It is noteworthy that a full set of year dummies cannot be included because they are perfectly collinear with electricity price instruments. However, to test the robustness of the results, in Section 5.1, I also present ordinary least squares (OLS) estimates with a full set of year dummies, excluding all control price variables. Further to testing the robustness, according to Griffin and Schulman (2005), time fixed effects are appropriate proxies for temporal energy efficiency improvements and other omitted variables that change similarly over time for all provinces. The results show that the estimates of the models with a full set of year dummies are not very different from the main estimates.

The coefficients in Equation (3.1) are first estimated using OLS regression with heteroscedasticity-robust standard errors. The OLS estimates, however, could still be affected by an endogeneity problem because an increase in electricity consumption might induce an increase in electricity price. This may result in a correlation between fuel prices and the error term, which causes the estimates to be biased. To address the potential endogeneity, I also employ an instrumental variable (IV) method by using instruments from the electricity supply side.

Around 70% of electricity supply in Thailand is generated from natural gas. Most natural gas consumed in Thailand originates from domestic reserves. In 2015, Thailand's natural gas imports accounted for 34% of its total natural gas supply (IEA, 2018). Power plants are the largest consumer of natural gas. More than 70% of natural gas produced in the country goes to power generation (Nakawiro and Bhattacharyya, 2007).

The natural gas price is therefore one of the major cost factors of electricity production. However, the fact that changes in electricity demand likely affect the domestic natural gas price makes the natural gas price inappropriate for being an electricity price instrument. Nevertheless, suitable price instruments could still be sourced from exogenous factors that are not affected by electricity consumption but influence natural gas price.

In Thailand, PTT is the only authorized company to transmit and distribute natural gas within the country. This provides PTT with sufficient market power to determine the natural gas price in the domestic market. PTT uses furnace oil price and exchange rates (and other factors) to index the wellhead gas price, which is the price at which PTT purchases natural gas from the producers (Nikomborirak, 2011; and PTT, 2018). The wellhead gas price is a key component in the domestic wholesale price of natural gas. Apart from the wellhead gas price, the wholesale price of natural gas comprises a marketing margin, the transmission tariff, and the distribution tariff.

The use of furnace oil price and exchange rates to index the wellhead gas price is based on the fact that furnace oil is a substitute for natural gas in industrial production and exchange rate affects the costs of importing natural gas (PTT, 2018). Furnace oil is among the petroleum products that are largely distilled domestically from imported crude oil (The Energy Policy and Planning Office, 2018). Furnace oil price in Thailand correlates highly with the world oil price. This suggests that the domestic furnace oil price is likely exogenous to the domestic natural gas price. Regarding the exchange rate, an appreciation of the Thai baht will cause imported natural gas to be cheaper relative to domestically produced natural gas. Therefore, an appreciation of Thai baht will likely be used as a criterion to reduce domestic natural gas price.

I use the real domestic furnace oil price and nominal Thai baht-US dollar exchange rate as instruments for the electricity price index. One component of electricity price in Thailand, the automatic tariff adjustment, varies with the costs of power generation. This electricity price component is usually revised approximately every four months. As a result, within the annual data, there are likely no significant lags in price adjustments when the production costs change. The results of the first-stage regression show that the instruments can explain much of the variation in the electricity price index, suggesting that the instruments are strong (see Table 3.2).

The fixed-effects model and other models in this study might be associated with potential reverse causality between electricity consumption and GDP. The problem is more likely to arise in the estimations for non-residential and total electricity than residential electricity. Bruns et al. (2014) perform a meta-analysis of 72 studies investigating Granger causality between energy use and economic output and find that when energy prices are controlled for, there is a genuine causal effect from output to energy use but not vice versa. Although the reverse causality could result in a simultaneity bias, the size of the bias tends not to be substantial. Csereklyei and Stern (2015) provide an assessment of potential simultaneity bias in energy-GDP elasticities induced by reverse causality. The bias is calculated to be around +0.05.

3.4.2 Five- and ten-year growth rates estimation

The growth rates model is specified to be comparable to the fixed-effects model in Equation (3.1). The growth rates model has the following form:

$$g\left(E_{i,t}\right) = \beta_0 + \left(\beta_1 + \beta_2 \ln \widetilde{Y_{i,t-n}}\right) * g\left(Y_{i,t}\right) + g\left(\boldsymbol{X'}_{i,t}\right)\boldsymbol{\vartheta} + \rho_t + \varepsilon_{i,t} \tag{3.2}$$

where n = 5 for t = 2011 and 2016 in the 5-year growth rates estimation, and n = 10 for t = 2016 in the 10-year growth rates estimation. $g()$ indicates the growth rate operator which gives average annual growth rate, e.g., $g(E) = (lnE_t - lnE_{t-n})/n$. The tilde (~) indicates that the variable has the sample mean subtracted, or $\ln \widetilde{Y_{i,t-n}} = \ln Y_{i,t-n} - \overline{\ln Y}_{t-n}$ where $\overline{\ln Y}$ is the sample mean of log of GDP per capita.

The interaction term between $\ln \widetilde{Y_{i,t-n}}$ and growth rate of GDP per capita allows the effect of growth rate of GDP per capita to vary with the log of GDP per capita at the beginning of the time period. A negative and significant β_2 would suggest that the effects of GDP growth on electricity consumption is lower for provinces that start with higher GDP per capita. The GDP elasticity in this specification follows $\beta_1 + \beta_2 \ln \widetilde{Y_{i,t-n}}$. That is, the GDP elasticity varies with the initial level of GDP. Because $\ln Y_{i,t-n}$ is demeaned, β_1 is the GDP elasticity at the sample mean of log GDP per capita.

The vector of control variables consist of the log of cooling degree days, and household size in the growth rate form. I do not include real electricity and natural gas prices because, given that all provinces share the same nominal prices, the cross-sectional variation in the real prices comes solely from difference in the inflation rates. For the same reason, the price variables are also not included in the cross-sectional and between estimations in Equation (3.4). ρ is the 5-year period fixed effects applied only to the five-year growth rates estimation. ρ equals to one for the period of 2011–2016 and zero otherwise. The growth rates models are estimated using only OLS because the exchange rate, one of the price instruments, is the same for all provinces.

It is important to note that although the model specification of Equation (3.2) corresponds to Equation (3.1) but assumes that if the growth rate of GDP per capita ($g(Y_{i,t})$) is zero, the log of the initial level of GDP per capita ($\ln \widetilde{Y_{i,t-n}}$) does not have an effect on the dependent variable. To relax this assumption, I also estimate the growth rates model that contains the independent term of $\ln \widetilde{Y_{i,t-n}}$:

$$g(E_{i,t}) = \beta_0 + (\beta_1 + \beta_2 \ln \widetilde{Y_{i,t-n}}) * g(Y_{i,t}) + \beta_3 \ln \widetilde{Y_{i,t-n}} + \beta_4 \ln E_{i,t-n} + g(\boldsymbol{X'}_{i,t})\boldsymbol{\vartheta} + \rho_t + \varepsilon_{i,t} \quad (3.3)$$

β_3 represents the effect of the initial level of GDP per capita at the sample mean when the growth rate of GDP per capita is zero. If β_3 is estimated to be negative and significant, the growth rate of electricity use, when economic growth is absent, is smaller in richer provinces. When the growth rate of GDP per capita is different from zero, the total effect of the log of initial level of GDP per capita equals $\beta_3 + \beta_2\, g(Y_{i,t})$.

Equation (3.3) also includes the initial electricity consumption per capita. A negative β_4 would suggest that electricity consumption grows more slowly in provinces with a higher initial consumption level. If that is the case, there is convergence in electricity consumption per capita between provinces over time, or beta convergence (Csereklyei and Stern, 2015; Stern, 2017).

3.4.3 Cross-sectional and between estimations

Model specifications for the cross-sectional and between estimations are as follows.

$$\ln E_i = \gamma_0 + \gamma_1 \ln Y_i + \gamma_2 (\ln Y_i)^2 + \boldsymbol{X'}_i \boldsymbol{\varphi} + \varepsilon_i \qquad (3.4)$$

The cross-sectional regression and between estimator have similar model specifications to the fixed-effects model. $\boldsymbol{X}$ in this specification contains the log of cooling degree days and household size. One challenge of the cross-sectional regression and between estimator is that both approaches are prone to omitted variable bias, leading to inconsistent estimates (Stern, 2010; and Burke and Abayasekara, 2018). The omitted variable bias arises from the fact that the time-invariant individual effects (which cannot be captured by the regressors) are incorporated into the error term. If the time-invariant individual effects correlate with the regressors, there will be a correlation between the regressors and the error term, which causes a bias. However, the results that I get from the cross-sectional regression and between estimator are comparable to the estimates from the fixed-effects and growth rates models, which are less likely to suffer from omitted variable bias.[20] It is expected that the long-run GDP elasticities estimated from the cross-sectional regression and between estimator are larger than the elasticities in the shorter run obtained from the fixed-effects and growth rates models.

3.4.4 Estimation with more control variables

While economic growth can increase electricity consumption directly due to an income effect, the effect of economic growth on electricity consumption may also be channeled through certain economic factors. Further to Sections 3.4.1 and 3.4.3, I also perform the fixed-effects, cross-sectional, and between estimation that include three possible channel controls. These variables are likely to be positively correlated with GDP and the

[20] In the growth rates models, the time-invariant individual effects are removed by differencing.

effects of these variables may as well cause the electricity-GDP elasticity to change with GDP.

The first variable is the share of manufacturing in GDP. This variable reflects economic structural change, the role of which has already been discussed in Section 3.2. As this variable tends to be associated exclusively with commercial activities, I do not include it in the residential equations. The second variable is urbanization. Urbanization is found to increase demand for electricity (Holtedahl and Joutz, 2004; O'Neill et al., 2012). This could be explained by the fact that urbanization reduces the costs of connecting to the grid and therefore accelerate energy transition towards electricity (Jones, 1991). In rich provinces where urbanization has reached or is about to reach its maximum, such in as Bangkok and Phuket, the impact of urbanization on electricity likely subsides. This may cause electricity consumption in these provinces to increase more slowly as GDP is growing. I use the share of urban population as a proxy for urbanization. The last additional control variable is electricity access. Similar to urbanization, the effect of electricity access likely diminishes as the rate of access approaches 100%. The share of households with electricity is used as a proxy for electricity access. However, because the degree of correlation between household size and urban population is very close to –1 (see Table 3.1),[21] I drop household size for the estimation in this section.

The regression in this section will provide estimates of GDP elasticity given that all the additional controls remain unchanged, in contrast to the estimation in Sections 3.4.1–3.4.3 that likely give the total effect of GDP on electricity consumption. It allows us to extract the direct effect of GDP from the total effect. More importantly, we can observe whether the pattern of change in electricity-GDP elasticity will transform once these channels are controlled for.

3.5 Data

The data of electricity consumption, electricity tariffs and subsidies were requested from the PEA and MEA, and collected from the website of the National Statistical Office (NSO, 2015; 2017). The electricity price indexes are calculated separately for residential,

[21] This should be expected because urbanization is likely associated with smaller household size.

non-residential, and total electricity use. All price indexes are normalised from the retail prices per kWh consisting of base tariffs, automatic tariff adjustment, and value added tax.

The GDP data were downloaded from the website of the Office of the National Economic and Social Development Board (NESDB, 2018). LPG price is the government's suggested retail price for a 15-kilogram tank in the BMR and Pathumthani obtained from Bank of Thailand (2018). The suggested price for other areas is unavailable. However, the price across country tends not to be very different from the suggested price in the BMR and Pathumthani. I deflate GDP, electricity price, and LPG price data to 2015 constant prices using the provincial consumer price index (CPI) collected from the website of the Ministry of Commerce (MOC, 2018).

The cooling degree days (CDDs) data are calculated from a base temperature of 26 degrees Celsius. CDDs indicates the number of degrees Celsius that a day's average temperature is above 26 degrees in a year. I obtained the temperature data from 125 weather stations across the country but excluded nine stations that have missing data. Next, I calculated provincial average CDDs from the remaining stations. The temperature data are obtained from the Thai Meteorological Department.

Household size is the proportion of population and number of households. The share of urban population was derived by dividing the number of population of all municipalities to the total population in each province. In Thailand, municipalities must have population density at least 1,500 per square kilometer. These data are provided by the Department of Provincial Administration (DOPA, 2018). The data of share of households with electricity are provided by the Ministry of Energy (MOE, 2018).

For the instrumental variables, the data for furnace oil price are collected from the website of the Energy Policy and Plan Office (EPPO, 2018). Finally, the exchange rate data come from the website of the International Monetary Fund (IMF, 2018).

Table 3.1 presents the correlation matrix of key variables. Unsurprisingly, some of the control variables, especially the share of urban population, share of manufacturing in GDP, and share of household with electricity, are positively correlated with GDP per capita and positively correlated with each other. However, the correlation coefficients of less than 0.7 are not so high that it will likely to cause a serious problem when including them in the same regression. Because the absolute value of the correlation coefficient between household size and share of urban population of 0.94 is very large, this suggests that the household size should be dropped when including the share of urban population in the estimation.

Table 3.1 Correlation matrix 2006–2016

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Ln Total electricity use per capita (kWh)	1.00								
(2)	Ln GDP per capita (real baht)	0.94	1.00							
(3)	Ln Total electricity price index (real)	–0.15	–0.12	1.00						
(4)	Ln LPG price (real)	–0.06	–0.09	0.37	1.00					
(5)	Ln CDD (degree Celsius)	0.42	0.30	0.04	0.15	1.00				
(6)	Household size	–0.56	–0.54	0.06	0.02	–0.20	1.00			
(7)	Ln Share of urban population	0.65	0.64	–0.06	–0.02	0.25	–0.94	1.00		
(8)	Ln Share of manufacturing in GDP	0.61	0.55	–0.09	–0.04	0.41	–0.36	0.36	1.00	
(9)	Ln Share of household with electricity	0.18	0.12	–0.08	–0.03	0.31	–0.22	0.20	0.13	1.00
	Number of observations: 814									

3.6 Results

3.6.1 Fixed-effects estimates

The short-run coefficients estimates obtained from the fixed-effects model are presented in Table 3.2. The table shows the OLS and IV estimates for residential, non-residential, and total electricity consumption, respectively. The lower part of Table 3.2 shows details of the first stage regression of the IV approach. The coefficients of both instruments have positive signs as expected and are highly significant. The magnitudes of the coefficients suggest that a 10% increase in furnace oil price and depreciation in the Thai baht against the

US dollar will increase electricity price by 1.7% and 0.2%, respectively. The *F*-statistics of 270–278 easily pass the Stock-Yogo test for weak instruments (Stock and Yogo, 2005). The overall estimates from the OLS and IV regressions are very similar.

The significantly negative coefficients of squared log of GDP per capita suggest that the GDP elasticities are lower at higher GDP levels. The base of the table shows the implied point estimates of GDP elasticities at the 25th, 50th, and 75th percentiles of GDP per capita. All categories of electricity consumption have declining GDP elasticities. The decline in the elasticities is most notable in non-residential electricity use where the elasticities at the 75th percentile of GDP per capita are around 60% of those at the 25th percentile. As the coefficients of squared log of GDP per capita are negative and significant, it is also suggest that the electricity-GDP relationship has an inverted U-shaped pattern. The estimated turning points at the bottom of the table suggest that the elasticities become negative at GDP per capita greater than around 0.7–0.8 million baht for total electricity use. This implies that once GDP per capita is beyond that level, electricity consumption per capita would decline as GDP per capita increases.

The results at the base of the table suggest that the short-run GDP elasticity of residential electricity use at the 50th percentile of GDP per capita is around 0.2. The values are higher at around 0.4 for non-residential and total electricity use. Overall, the results show that electricity consumption is likely income inelastic in the short run. The estimates are close to the income elasticity of electricity demand estimated by Burke and Abayasekara (2018) for the U.S. but larger than that estimated by Burke and Kurniawati (2018) for Indonesia.[22]

[22] Burke and Abayasekara (2018) and Burke and Kurniawati (2018) apply a first-differenced model to obtain short-run estimates. I get lower average elasticities from a first-differenced model compared to the elasticities at the 50th percentile of GDP per capita from the fixed-effects model. The first-differenced GDP elasticities are around 0.1 for residential, and 0.2 for non-residential and total electricity use. These estimates lie between those of Burke and Abayasekara (2018) and Burke and Kurniawati (2018). My results suggest that a first-differenced model tends to provide estimates for the shorter run compared to a fixed-effects model.

Table 3.2 Fixed-effects estimates

Dependent variable: Ln Electricity consumption per capita (kWh)	Residential		Non-residential		Total	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Ln Real GDP per capita$_{i,t}$	1.25***	1.24***	3.14***	3.27***	2.17***	2.26***
	(0.21)	(0.20)	(0.48)	(0.46)	(0.38)	(0.36)
Squared Ln Real GDP per capita$_{i,t}$	–0.05***	–0.05**	–0.12***	–0.12***	–0.08***	–0.08***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Ln Real Electricity price index$_{i,t}$	–0.57***	–0.59***	–0.95***	–0.73***	–0.80***	–0.62***
	(0.05)	(0.06)	(0.13)	(0.17)	(0.10)	(0.13)
Ln Real LPG price$_{i,t}$	0.27***	0.27***	0.30***	0.27***	0.26***	0.25***
	(0.02)	(0.02)	(0.05)	(0.05)	(0.04)	(0.04)
Ln CDD$_{i,t}$	0.04***	0.08***	0.07***	0.06***	0.06***	0.05***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Household size	–0.01***	–0.01***			–0.02***	–0.02***
	(0.002)	(0.002)			(0.004)	(0.004)
Time dummies for electricity price subsidy$_t$	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects$_i$	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.997	0.997	0.996	0.996	0.997	0.997
Observations	814	814	814	814	814	814
Instrumented variable: Electricity price index (real)$_{i,t}$. Instrument: Ln Furnace oil price (real baht/litre)$_{i,t}$, and Ln Exchange rate (baht/US dollar)$_t$						
First-stage coefficients						
Ln Furnace oil price (real baht/litre)$_{i,t}$		0.17***		0.17***		0.17***
Ln Exchange rate (baht/US dollar)$_t$		0.01***		0.01***		0.01***
F statistic on instruments		270.0		277.7		275.2
GDP elasticities at xth percentile of GDP per capita						
25th	0.24***	0.24***	0.53***	0.54***	0.41***	0.42***
50th	0.20***	0.20***	0.43***	0.43***	0.35***	0.35***
75th	0.15***	0.15***	0.30***	0.30***	0.26***	0.26***
Real GDP per capita at turning point of GDP elasticity (baht)	751,350	765,078	546,969	508,026	776,009	700,816

Notes: Robust standard errors are presented in parentheses. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively. Coefficients on constants are not reported. Reported R^2 includes explanatory power of the province fixed effects. xth percentile of ln GDP per capita are calculated from the GDP per capita in 2006. Real GDP per capita at turning point of GDP elasticity is out of sample when it is greater than the maximum values of real GDP per capita in the full sample of 1,394,915 million baht.

The coefficients of control variables make sense. Higher electricity price leads to lower electricity consumption with the short-run price elasticity around –0.6 to –1.0. These estimates are larger than the results of Burke and Abayasekara (2018) and Burke and Kurniawati (2018). The coefficients of LPG price are positive as theory would predict, with a cross-price elasticity of around 0.3. Warmer temperature is associated with greater electricity demand. The degrees of responsiveness to higher temperature are quite similar between residential and non-residential demand. Finally, electricity consumption per capita is greater for provinces with smaller average household size. This is likely because larger households can save electricity use per person by sharing electricity services.

In Table 3.3, I estimate the fixed-effects model with different numbers of control variables to test the robustness of the results. The first column of each demand category shows the estimates when no control variables are included, except the province fixed effects. This model specification gives significantly larger GDP elasticities but the GDP elasticities still exhibit a decline in values as the economy grows since the coefficients of squared log of GDP per capita are negative and significant. Year fixed-effects are introduced in columns (2), (5), and (8) to take into account time-specific shocks. Columns (3), (6), and (9) have year fixed-effects and other controls except the price-related control variables. The estimates of GDP elasticities in the second and third columns of each demand category are very close to the estimates in Table 3.2. This suggests that the results in Table 3.2 are robust.

Table 3.3 Robustness check for the fixed-effects estimation

Dependent variable: Ln Electricity consumption per capita (kWh)	Residential			Non-residential			Total		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln Real GDP per capita$_{i,t}$	4.84*** (0.59)	1.58*** (0.20)	1.45*** (0.20)	6.79*** (0.62)	3.57*** (0.47)	3.50*** (0.47)	5.81*** (0.54)	2.73*** (0.38)	2.48*** (0.37)
Squared Ln Real GDP per capita$_{i,t}$	–0.17*** (0.03)	–0.06*** (0.01)	–0.06*** (0.01)	–0.25*** (0.03)	–0.14*** (0.02)	–0.14*** (0.02)	–0.21*** (0.02)	–0.10*** (0.02)	–0.09*** (0.02)
Ln CDD$_{i,t}$			0.04** (0.02)			0.15*** (0.03)			0.11*** (0.02)
Household size			–0.01*** (0.002)						–0.02*** (0.004)
Year fixed effects$_t$		Yes	Yes		Yes	Yes		Yes	Yes
Province fixed effects$_i$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.94	0.996	0.997	0.99	0.996	0.996	0.98	0.997	0.997
Observations	814	814	814	814	814	814	814	814	814
GDP elasticities at xth percentile of GDP per capita									
25th	1.10***	0.26***	0.24***	1.37***	0.54***	0.53***	1.25***	0.45***	0.42***
50th	0.95***	0.21***	0.19***	1.15***	0.43***	0.42***	1.07***	0.36***	0.34***
75th	0.77***	0.14***	0.13***	0.89***	0.28***	0.27***	0.84***	0.25***	0.24***
Real GDP per capita at turning point of GDP elasticity (baht)	Out of sample	495,275	515,073	922,871	417,929	415,727	1,154,828	513,706	535,754

Notes: Robust standard errors are presented in parentheses. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively. Coefficients on constants are not reported. Reported R^2 includes explanatory power of the province fixed effects. xth percentile of ln GDP per capita are calculated from the GDP per capita in 2006. Real GDP per capita at turning point of GDP elasticity is out of sample when it is greater than the maximum values of real GDP per capita in the full sample of 1,394,915 million baht.

3.6.2 Growth rates estimates

Tables 3.4 and 3.5 present results of the five- and ten-year growth rates estimation, respectively. The estimates from Equation (2) are shown in columns (1), (3), and (5) while the rest present estimates from Equation (3) where the independent term of the initial level of GDP per capita and the initial electricity consumption are included. Overall, the estimation of Equation (2) provides slightly larger GDP elasticities at the sample mean of log GDP per capita for both the five- and ten-year growth rates models. The five-year GDP elasticities of around 0.2–0.3 are quite close to the fixed-effects elasticities at the 50th percentile of GDP per capita while the ten-year GDP elasticities are larger. Furthermore, the estimation of Equation (2) suggest that the GDP elasticity is likely lower at the higher initial level of GDP per capita as the coefficients of the interaction term are negative and mostly significant.

However, when the logs of initial GDP and electricity consumption per capita are included, the coefficients of the interaction term become insignificant. That is, once allowing the effect of initial GDP per capita to be non-zero when economic growth is absent, there is no evidence that the GDP elasticities decline with the initial level of GDP per capita.[23] The results show evidence of beta convergence for non-residential and total electricity use, but not for residential electricity use. Coefficients of the control variables in Tables 3.4 and 3.5 are sparsely significant.

Comparing the fixed-effects and growth rates estimates, it is evident that the standard errors in the growth-rates estimates are significantly larger. Presumably, this is largely a result of the smaller degrees of freedom of the growth rates models and is potentially the key factor causing most coefficients to be insignificant. However, large standard errors are not observed in the cross-sectional and between estimations that are subject to the same degrees of freedom of the growth rates models. This seems to suggest that cross-sectional variation in levels is more dominant than that in growth rates and can compensate for the reduced degrees of freedom from the fixed-effects estimation.

[23] The results are similar when the log of initial GDP per capita is included but the log of initial electricity consumption is excluded.

Table 3.4 Five-year growth rate estimates

Dependent variable: Electricity consumption per capita growth rate	Residential		Non-residential		Total	
	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita growth rate	0.20***	0.19***	0.36***	0.25***	0.28***	0.20***
	(0.04)	(0.04)	(0.09)	(0.06)	(0.06)	(0.05)
GDP per capita growth rate*Ln GDP per capita$_{t-5;\ \mathrm{sample\ demeaned}}$	–0.05	–0.0002	–0.35***	0.09	–0.21***	0.11
	(0.04)	(0.05)	(0.07)	(0.09)	(0.06)	(0.07)
Ln GDP per capita$_{t-5;\ \mathrm{sample\ demeaned}}$		0.002		0.002		0.0001
		(0.002)		(0.01)		(0.01)
Ln Electricity use per capita $_{t-5}$		–0.01		–0.02***		–0.01***
		(0.01)		(0.004)		(0.01)
CDD growth rate	0.04	0.04	0.16**	0.09*	0.13**	0.08*
	(0.03)	(0.03)	(0.07)	(0.05)	(0.05)	(0.04)
Household size growth rate	–0.01	–0.005			–0.02***	–0.01**
	(0.01)	(0.01)			(0.01)	(0.01)
Dummy for the 2011–2016 period	0.01	0.01*	–0.03**	–0.02**	–0.02**	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.31	0.33	0.29	0.54	0.28	0.53
Observations	148	148	148	148	148	148

Notes: Robust standard errors are presented in parentheses. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively. Coefficients on constants are not reported.

Table 3.5 Ten-year growth rate estimates

Dependent variable: Electricity consumption per capita growth rate	Residential		Non-residential		Total	
	(1)	(2)	(3)	(4)	(5)	(6)
GDP per capita growth rate	0.26***	0.26***	0.61***	0.51***	0.57***	0.40***
	(0.06)	(0.06)	(0.14)	(0.09)	(0.14)	(0.07)
GDP per capita growth rate*Ln GDP per capita$_{t-10;\ \text{sample demeaned}}$	–0.09**	–0.06	–0.50***	–0.03	–0.47***	0.04
	(0.04)	(0.06)	(0.10)	(0.10)	(0.10)	(0.08)
Ln GDP per capita$_{t-10;\ \text{sample demeaned}}$		0.002		0.01		0.004
		(0.002)		(0.01)		(0.01)
Ln Electricity use per capita $_{t-10}$		–0.004		–0.02***		–0.01***
		(0.004)		(0.004)		(0.005)
CDD growth rate	–0.03	–0.03	0.30**	0.05	0.27**	0.01
	(0.04)	(0.04)	(0.13)	(0.07)	(0.13)	(0.05)
Household size growth rate	–0.01**	–0.01**			–0.03*	–0.02*
	(0.01)	(0.01)			(0.02)	(0.01)
R^2	0.47	0.48	0.49	0.71	0.50	0.74
Observations	74	74	74	74	74	74

Notes: Robust standard errors are presented in parentheses. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively. Coefficients on constants are not reported.

3.6.3 Cross-section and between estimates

Table 3.6 presents the long-run estimates obtained from the cross-sectional regression. The estimates are presented for the years 2006 and 2016, the first and final years of the study period. The GDP elasticities estimated for both years are quite similar. The cross-sectional estimation provides greater GDP elasticities than the fixed-effects and growth rates models as expected. The cross-sectional estimates suggest that the residential electricity demand is still income inelastic in the long run, with the estimated elasticity at the 50^{th} percentile of GDP per capita around 0.6. On the other hand, non-residential and total electricity demand are found to be income elastic in the long-run. The estimated long-run GDP elasticities for non-residential and total electricity demand at the 50^{th} percentile of GDP per capita are around 1.4 and 1.1, respectively.

Similar to the fixed-effects estimates, the coefficients of quadratic log GDP per capita are negative and significant, except only for the coefficient for total electricity consumption in 2006. In general, the results suggest that, in the long run, the GDP elasticities likely decline as provinces become richer. One difference from the fixed-effects estimates is that the residential GDP elasticities decline faster with GDP than the non-residential elasticities. The residential GDP elasticities at the 75^{th} percentile of GDP per capita decrease by around 30% from the elasticities at the 25^{th} percentile of GDP per capita. The number is around 16–20% in the case of non-residential elasticities.

The coefficients the log of CDDs are larger than the fixed-effects estimates suggesting that the degree of adaptation to warmer temperature is greater in the long-run. The coefficients of household size are only significant for residential demand. High values of R^2 in all columns show that the large extent of variation in energy use between provinces can be explained by differences in GDP and temperature.

The between estimates are shown in Table 3.7. The first column of each category of electricity use presents the estimates using the whole sample. The results in the second and third columns are estimated from the two sub-samples: 2006–2011 and 2012–2016. The coefficients of quadratic log GDP per capita are, again, negative and significant. The between estimator gives very similar results to the cross-sectional estimation. The GDP elasticities at the 50th percentile of GDP per capita are around 0.6–0.7 for residential electricity, 1.4–1.5 for non-residential electricity, and 1.1–1.2 for total electricity. This suggests that the relationship between electricity use and GDP is quite stable over time. The long-run GDP elasticities of total electricity demand estimated in this study are not very different from the income elasticities estimated for other middle income countries, e.g., Sri Lanka (Amarawickrama and Hunt, 2008), South Africa (Inglesi-Lotz, 2011), and Turkey (Arisoy and Ozturk, 2014).

Table 3.6 Cross-sectional estimates

Dependent variable: Ln Electricity consumption per capita (kWh)$_i$	Residential		Non-residential		Total	
	2006	2016	2006	2016	2006	2016
	(1)	(2)	(3)	(4)	(5)	(6)
Ln Real GDP per capita$_i$	2.82***	3.35***	3.99***	5.04***	2.08**	3.29***
	(0.49)	(0.54)	(0.94)	(1.14)	(0.82)	(0.92)
Squared Ln Real GDP per capita$_i$	–0.10***	–0.12***	–0.11***	–0.16***	–0.04	–0.10**
	(0.02)	(0.04)	(0.04)	(0.05)	(0.03)	(0.04)
Ln CDD$_i$	0.18***	0.33***	0.54***	0.64***	0.41***	0.54***
	(0.06)	(0.07)	(0.16)	(0.19)	(0.11)	(0.13)
Household size$_i$	–0.03**	–0.02*			–0.03	–0.02
	(0.01)	(0.01)			(0.02)	(0.01)
R^2	0.88	0.88	0.91	0.92	0.92	0.93
Observations	74	74	74	74	74	74
GDP elasticities at x^{th} percentile of GDP per capita						
25^{th}	0.69***	0.71***	1.55***	1.49***	1.13***	1.15***
50^{th}	0.59***	0.62***	1.43***	1.38***	1.08***	1.08***
75^{th}	0.47***	0.49***	1.30***	1.19***	1.03***	0.97***
Real GDP per capita at turning point of GDP elasticity (baht)	Out of sample	1,319,244	Out of sample	Out of sample	Out of sample	Out of sample

Notes: Robust standard errors are presented in parentheses. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively. Coefficients on constants are not reported. x^{th} percentile of Ln GDP per capita are calculated from the GDP per capita in 2006 for the 2006 estimates and calculated from the GDP per capita in 2016 for the 2016 estimates. Real GDP per capita at turning point of GDP elasticity is out of sample when it is greater than the maximum values of real GDP per capita in the full sample of 1,394,915 million baht.

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Table 3.7 Between estimates

Dependent variable: Ln Electricity consumption per capita $(kWh)_i$	Residential			Non-residential			Total		
	2006–2016	2006–2011	2012–2016	2006–2016	2006–2011	2012–2016	2006–2016	2006–2011	2012–2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln Real GDP per $capita_i$	3.49***	3.23***	3.68***	5.01***	4.49***	5.43***	3.27***	2.77***	3.67***
	(0.48)	(0.47)	(0.52)	(0.92)	(0.92)	(1.00)	(0.78)	(0.79)	(0.82)
Squared Ln Real GDP per $capita_i$	–0.13***	–0.11***	–0.13***	–0.16***	–0.14***	–0.17***	–0.09***	–0.07**	–0.11***
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Ln CDD_i	0.22***	0.21***	0.22***	0.57***	0.60***	0.51***	0.45***	0.46***	0.42***
	(0.06)	(0.07)	(0.06)	(0.16)	(0.17)	(0.15)	(0.11)	(0.12)	(0.11)
Household $size_i$	–0.02	–0.02	–0.02*				–0.02	–0.02	–0.01
	(0.01)	(0.01)	(0.01)				(0.02)	(0.02)	(0.01)
R^2	0.88	0.88	0.88	0.92	0.91	0.92	0.93	0.92	0.93
Observations	814	444	370	814	444	370	814	444	370
GDP elasticities at x^{th} percentile of GDP per capita									
25^{th}	0.80***	0.76***	0.75***	1.65***	1.58***	1.58***	1.26***	1.20***	1.23***
50^{th}	0.67***	0.64***	0.65***	1.48***	1.44***	1.45***	1.17***	1.13***	1.15***
75^{th}	0.53***	0.51***	0.50***	1.30***	1.28***	1.25***	1.06***	1.04***	1.02***
Real GDP per capita at turning point of GDP elasticity (baht)	1,158,539	1,275,464	1,111,237	Out of sample	Out of sample	Out of sample	Out of sample	Out of sample	Out of sample

Notes: Robust standard errors are presented in parentheses. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively. Coefficients on constants are not reported. Reported R^2 is between R^2. x^{th} percentile of Ln GDP per capita are calculated from the GDP per capita in 2006 for the 2006–2016 and 2006–2011 estimates and calculated from the GDP per capita in 2012 for the 2012–2016 estimates. Real GDP per capita at turning point of GDP elasticity is out of sample when it is greater than the maximum values of real GDP per capita in the full sample of 1,394,915 million baht.

3.6.4 Results with more control variables

Table 3.8 presents estimates with three additional control variables: the log of share of manufacturing in GDP, the log of share of urban population, and the log of share of household with electricity. As mentioned earlier, household size is excluded from the estimations due to the high degree of correlation with the log of share of urban population. The coefficients are estimated using the OLS fixed-effects, cross-sectional, and between estimation. The results tend to suggest that a decrease in the share of manufacturing in GDP causes a decrease in non-residential and total electricity consumption, consistent with the fact that manufacturing is more electricity intensive compared with agriculture and services. Urbanization tends to increase electricity use per capita, especially in households. There is no strong evidence that an improvement in electricity access will increase electricity use per capita significantly. This might be because the variation in electricity access in the dataset is relatively inconsiderable.

All models in Table 3.8 give very close GDP elasticities compared to the corresponding original models. The results still suggest that GDP elasticities decline with GDP. The rates of decline are not significantly different from the original models. Two key implications can be drawn from these observations. First, the impact of changes in GDP on electricity largely occurs directly rather than channeled through other economic factors. Second, the electricity-GDP elasticity tends to decrease with GDP even when structural change, urbanization, and electricity access remain constant. In the next section, I discuss what can potentially explain a decline in the elasticity.

Table 3.8 Estimates with more control variables

Dependent variable: Ln Electricity consumption per capita (kWh)$_i$	Residential			Non-residential			Total		
	Fixed-effects (OLS)	Cross-sectional 2016	Between estimator 2006–2016	Fixed-effects (OLS)	Cross-sectional 2016	Between estimator 2006–2016	Fixed-effects (OLS)	Cross-sectional 2016	Between estimator 2006–2016
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln Real GDP per capita	1.31***	3.44***	3.51***	3.02***	4.59***	4.55***	2.27***	3.28***	3.21***
	(0.21)	(0.52)	(0.47)	(0.46)	(1.06)	(0.93)	(0.37)	(0.83)	(0.73)
Squared Ln Real GDP per capita	–0.05***	–0.12***	–0.13***	–0.11***	–0.15***	–0.14***	–0.08***	–0.10***	–0.09***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.02)	(0.04)	(0.03)
Ln Real Electricity price index	–0.58***			–0.97***			–0.82***		
	(0.05)			(0.13)			(0.10)		
Ln Real LPG price	0.28***			0.31***			0.28***		
	(0.02)			(0.05)			(0.03)		
Ln CDD$_i$	0.03***	0.32***	0.21***	0.05***	0.41**	0.41**	0.05***	0.41***	0.34***
	(0.01)	(0.07)	(0.06)	(0.02)	(0.17)	(0.16)	(0.01)	(0.13)	(0.12)
Ln Share of manufacturing in GDP				0.03	0.17***	0.19***	0.02	0.10**	0.11**
				(0.02)	(0.06)	(0.07)	(0.01)	(0.04)	(0.05)
Ln Share of urban population	0.04***	0.15***	0.16**	0.05	0.09	0.12	0.04*	0.10	0.11
	(0.01)	(0.06)	(0.08)	(0.03)	(0.10)	(0.13)	(0.02)	(0.08)	(0.11)
Ln Share of household with electricity	0.33***		0.01	0.67***		–3.35	0.62***		–1.21
	(0.09)		(1.63)	(0.16)		(3.18)	(0.12)		(2.50)
R^2	0.997	0.89	0.89	0.996	0.93	0.93	0.997	0.94	0.94
Observations	814	74	814	814	74	814	814	74	814
GDP elasticities at x^{th} percentile of Ln GDP per capita									
25^{th}	0.25***	0.70***	0.78***	0.52***	1.37***	1.49***	0.43***	1.11***	1.20***
50^{th}	0.20***	0.60***	0.65***	0.43***	1.26***	1.34***	0.36***	1.03***	1.10***
75^{th}	0.15***	0.46***	0.50***	0.30***	1.09***	1.17***	0.27***	0.92***	0.99***
Real GDP per capita at turning point of GDP elasticity (baht)	730,018	1,092,664	994,800	582,859	Out of sample	Out of sample	774,224	Out of sample	Out of sample

Notes: Robust standard errors are presented in parentheses. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively. Coefficients on constants are not reported. The fixed-effects estimation also includes time dummies for electricity price subsidy. Reported R^2 for the fixed-effects estimation includes explanatory power of the province fixed effects. Reported R^2 for the between estimator is between R^2. Real GDP per capita at turning point of GDP elasticity is out of sample when it is greater than the maximum values of real GDP per capita in the full sample of 1,394,915 million baht.

3.6.5 Possible explanations for declining electricity-GDP elasticity

As mentioned earlier, one factor that could cause electricity-GDP elasticity to decline is improvements in efficiency of electricity use. Efficiency of electricity use likely improves over time due to advances in technology. This may cause electricity demand to grow more slowly with GDP, all else being equal.[24] It is also possible that electricity users in richer provinces have better access to and better capacity to obtain electricity saving technologies such as LED lighting, solar panels and solar batteries, motion sensors, and more efficient electrical appliances and machines. Improvements in efficiency of electricity use allow less proportion of income to be dedicated to the same level of electricity services.

For residential users in particular, the declining GDP elasticity might also be explained by the fact that the investments in household electrical appliances are different at different income levels. Residential electricity use tends to increase rapidly when many households can afford certain appliances for the first time, e.g., refrigerators, air conditioners, and washing machines. The growth of residential electricity use may then decline once many households possess all the essential home appliances. Wolfram et al. (2012) show that there is an S-shaped relationship between income and household appliance acquisitions in developing countries. That is, the increasing growth of appliance acquisitions in response to an increase in income exists up to a certain income level after which the growth of appliance acquisitions declines. Furthermore, Fouquet (2014) points out that household income elasticity for energy services decreases in the long run due to saturation effects: as income rises, a declining share of budget is spent on energy services once the consumption level has passed a certain level. The saturation effects are usually found in other necessary goods.

Other potential reasons include environmental awareness. Franzen and Meyer (2010) find that people with a higher income likely show higher environmental awareness. It is also possible that people in richer provinces are more exposed to energy conservation campaigns that in turn affect their electricity use behaviors. Relevant government campaigns implemented in Thailand include the provision of energy audits and retrofit investment consultations to commercial and industrial buildings, and a promotion of energy conservation awareness through various forms of media and school-based activities (World Bank, 2006).

[24] Efficiency improvements are likely associated with the rebound effect (an increase in energy use due to a decrease in the effective price; see, for example, Greening et al. (2000) and Gillingham et al. (2016)). According to Gillingham et al. (2016), the existing literature does not provide strong evidence that energy efficiency gains will be fully offset by the rebound effect.

In Thailand's case, it is possible that the progressive structure of the electricity tariff also contributes to declining elasticity because consumers reduce their electricity consumption when charged a higher price. However, this effect tends to be largely limited to only residential electricity consumption. Most non-residential users face flat rate tariffs and we can still observe declining GDP elasticity in non-residential electricity use.

3.6.6 Projection of electricity demand

In this section, I calculate a projection of electricity demand for national total electricity use by employing the estimated coefficients from column (7) of Table 3.5 and the forecasted GDP growth from PDP2015. Figure 3.5 compares the annual average growth rates of my projection with the projection in PDP2015 for the BAU case. My projection suggests declining power demand growth rates from 3.9% over 2016–2021 to 3.4% over 2031–2036. This is based on a decline in the elasticity from 0.97 in 2016 to 0.82 in 2036. My growth rate estimates are slightly lower than the PDP during 2016–2021 and 2031–2036 but higher during 2021–2031.

Nevertheless, as pointed out earlier, the PDP's forecast includes the result of potential energy savings from the implemented measures, whereas my estimates do not take into account any demand shocks that happen after 2016. If the future energy savings are considered, my growth rate projection will be lower than what presented in Figure 3.5.

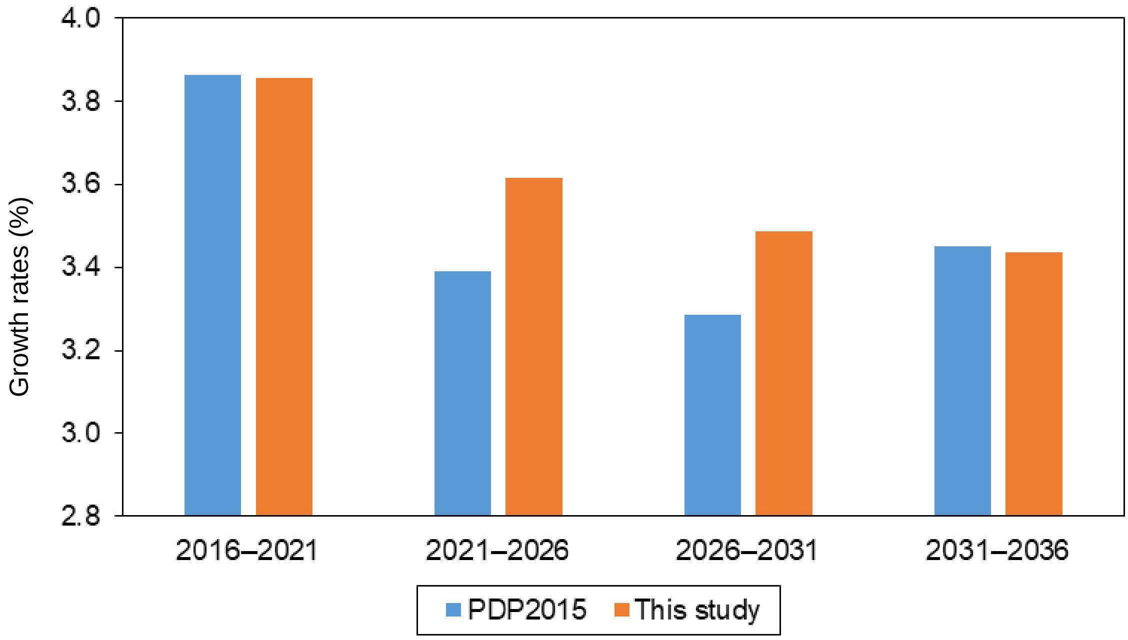

Figure 3.5 Annual average growth rates of the forecasted electricity demand per capita from PDP2015 and this study. Notes: PDP's forecast is the forecast of business-as-usual electricity demand. The population growth projection from NESDB (2018b) is used to adjust the forecasted growth rates of GDP levels and electricity demand shown in PDP2015 into a per-capita term. In my forecast, I calculate the power demand in 2016 using the actual electricity consumption from the dataset. Then, I apply the estimated elasticity in Column (7) of Table 3.5 and the forecasted GDP growth from PDP2015 to project power demand in the following years.

Note: The average growth rate of total electricity demand during 2031–2036 in PDP2015 is 3.16, lower than the growth rates during 2026–2031 and 2021–2026 which are 3.47 and 3.29, respectively. However, the growth rate for the period 2031–2036 when converted into a per-capita term become higher than the other two periods due to projected negative population growth.

As my results suggest lower electricity-GDP elasticity in provinces with higher GDP per capita, if the economy in all provinces is assumed to grow at the same rate, electricity demand will grow more slowly in richer provinces. Figure 3.6 presents the growth rate projection of electricity demand for three provinces/regions: the Bangkok Metropolitan Region (BMR; consisting of Bangkok, Nonthaburi, and Samutprakan), Lampang, and Buriram) by assuming GDP per capita growth rate in all provinces at 4% per annum. These provinces represent the GDP per capita at the 1st, 5th, and 10th deciles, respectively. The graph shows that in 2036, the power demand growth rate in the BMR will be 2.4%, declining from 3.0% in 2016. The growth rates are higher in the other two provinces at 4.0 and 4.4% in 2036. Between the BMR and Buriram, the difference of implied electricity demand growth rates in the same year is 2%.

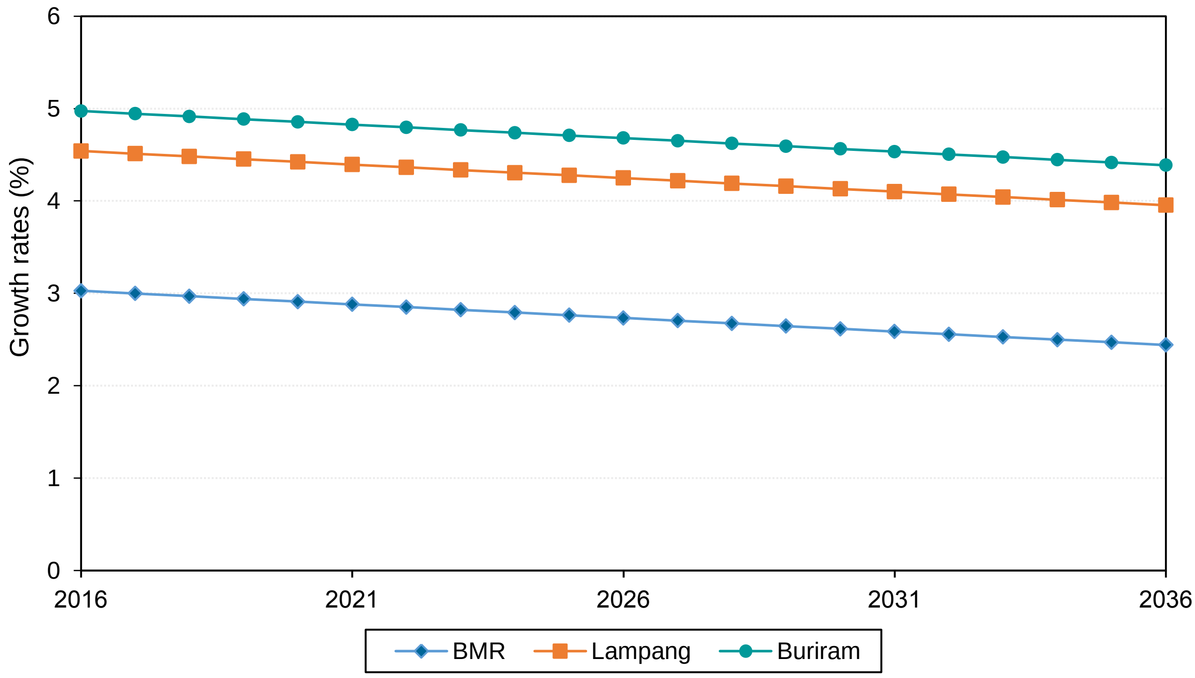

Figure 3.6 Estimated growth rates of electricity demand assuming 4% GDP per capita growth rate for the BMR, Lampang, and Buriram. Notes: The estimates are predications from the regression in column (7) of Table 3.5.

3.7 Conclusion

This study has used Thailand's provincial data from 2006 to 2016 to estimate the GDP elasticity of electricity demand. Different econometric approaches are applied to obtain the elasticities in the short run, in 5- and 10-year periods, and in the long run. The non-residential electricity demand is found to have greater elasticity than the residential demand. The residential demand is income inelastic in both the short run and long run, with an elasticity of around 0.2 in the short run and 0.6–0.7 in the long run. On the other hand, the non-residential demand is income inelastic in the short run but income elastic in the long run with a short-run elasticity of 0.4 and long-run elasticity of 1.4–1.5. The GDP elasticity of total electricity demand is around 0.4 in the short run and 1.1–1.2 in the long run.

The key findings are that, as GDP per capita grows, the GDP elasticity of electricity demand will be lower. Similar findings are found for residential, non-residential, and total electricity demand. A reduction in the GDP elasticity with GDP levels is observed in the short-run and long-run estimates. Although the 5- and 10-year estimates do not show evidence that higher initial GDP per capita is associated with lower GDP elasticity, the results suggest that if the initial level of GDP per capita is higher, the growth rates of non-residential and total electricity demand are likely lower.

The findings imply that projections of electricity demand employing declining GDP elasticity will likely be more precise than the projections that are based on constant GDP elasticity. Thailand's power development plan 2015–2036 has already incorporated declining GDP elasticity into the electricity demand projection. However, the question of how much new demand will arise in each area is also an important question for electricity infrastructure planning because it is normally costly and inefficient to transmit electricity over long distances. My findings suggest that, with the same economic growth rate, electricity demand likely grows faster in provinces with relatively low levels of GDP per capita. This is the case even when urbanization, structural change, and electricity access are controlled for. Therefore, the use of the use of varying elasticity between provinces may be necessary to forecast electricity demand in Thailand.

The results do not incorporate the effects of future economic factors that will likely impact electricity demand in Thailand. Some factors will likely cause the GDP elasticity of electricity demand to decline even faster with GDP per capita than that is estimated in this study while other factors might have an opposite impact. The examples of the factors to likely accelerate the reduction in the GDP elasticity are as follows. First, the importance of manufacturing in the Thai economy will likely continue declining while the service sector, which is less intensive in electricity use, will become more dominant. The contribution of manufacturing to Thai GDP peaked in 2010 at 31% and declined continuously afterwards to 27% in 2017 (World Bank, 2018). Over the past decade, information and communication, tourism, and financial and insurance have been among the fastest-growing industries in

Thailand while many key manufacturing industries (e.g., food products, textiles, and electronics) have grown much more slowly (NESDB, 2018). Second, the Thai government has set a target to reduce electricity consumption by 90 TWh per year by 2036, compared to the business-as-usual scenario. The planned measures include introducing tax and monetary incentives to encourage the use of high efficiency appliances, defining industrial factory and building energy codes, and removing or revising energy price subsidies (The Energy Policy and Planning Office, 2015).

On the other hand, the electrification of road transport might retard a decline in GDP elasticity. Economic growth likely induces an increase in electric vehicle uptake in the future and will place upward pressure on electricity consumption. This will also likely equalize the electricity-GDP elasticities of different provinces as richer provinces tend to be quicker at adopting electric vehicles. However, an increase in electricity demand from the grids may partly be offset by the use of rooftop solar panels.

A Appendix

A.1 Structure of electricity pricing in Thailand

In Thailand, electricity is provided to end users mainly by two retail providers. Each of these providers supplies electricity in different areas. The MEA provides electricity in the Greater Bangkok, which covers Bangkok, Nonthaburi, and Samutprakan. The PEA has the service areas covering the rest of the country. Both the MEA and PEA apply the same electricity tariffs which are imposed by the National Energy Policy Council.

The electricity charges in Thailand consist of three components: base tariffs, automatic tariff adjustment (usually referred to as F_t in Thailand), and value added tax (VAT). The base tariffs are charges per kWh use per month plus a lump-sum service fee. The base tariffs are different for each type of customers: residential,[25] small general service, medium general service, large general service, specific business service (hotels, guest houses,

[25] Residential customers by the definition of PEA and MEA are households and other dwelling places, monasteries, house of priest, and religious places of worship, including their compound, through a single Watt-hour meter. Businesses with residential are not included in the residential customers.

and lodging business), non-profit organization, agricultural pumping, and temporary service. The base tariffs for residential and some of small general service users varies with the amount of electricity use: the more electricity is used, the higher the marginal rate will be. For the rest of the users, except for the temporary services, the base tariffs vary mainly with voltage levels. From 2006 to 2016, the base tariffs were adjusted three times: in July 2011, June 2012, and November 2015. The adjustments in 2011 and 2015 increased the rates for all users. On the other hand, the adjustment in 2012 maintained the rates for residential and small general service users but slightly reduced the rates for other users. Table A.1 present the base tariff for residential users from 2006 to 2015.

Table A.1 Residential Electricity Base Tariff (baht/kWh)

Types of users	**Jan 2006 – June 2011**	**July 2011 – October 2015**	**November – December 2015**
≤ 150 kWh per month			
$1^{st} – 5^{th}$ kWh	0	1.8632	2.3488
$6^{th} – 15^{th}$ kWh	1.3576	1.8632	2.3488
$16^{th} – 25^{th}$ kWh	1.5445	2.5026	2.9882
$26^{th} – 35^{th}$ kWh	1.7968	2.7549	3.2405
$36^{th} – 100^{th}$ kWh	2.1800	3.1381	3.6237
$101^{th} – 150^{th}$ kWh	2.2734	3.2315	3.7171
Service fee	8.19 baht/month	8.19 baht/month	8.19 baht/month
> 150 kWh per month			
$1^{st} – 150^{th}$ kWh	1.8047	2.7628	3.2484
$151^{st} – 400^{th}$ kWh	2.7781	3.7362	4.2218
401^{st} kWh onwards	2.9780	3.9361	4.4217
Service fee	40.90 baht/month	38.22 baht/month	38.22 baht/month

Souce: PEA

The second tariff component, F_t, is the charge for each kWh on top of the base tariffs. It is used to adjust the electricity price of each kWh to make the price correspond to the actual costs of power generation at that time. F_t is a constant charge, meaning that it does not vary with the amount of electricity consumption. The same rate of F_t is applied for all types of users. F_t can be either positive or negative. If it is negative, the customers pay less than the base tariff. F_t is usually revised approximately every four months. Finally, VAT is added to the sum of base tariffs and F_t. Over the study period, the VAT rate had remained unchanged at 7%.

In Thailand, electricity customers receive their electricity bills at the end of each month. Therefore, they have the opportunity to adjust their electricity use every month based on the data that they receive from the bills. Also, electricity tariff adjustments are normally announced on newspapers and television channels before time so a number of users are likely to be aware of the coming electricity price changes and able to plan their electricity consumption in advance.

To support low-income families, in August 2008, the government started an electricity price subsidy scheme for small residential electricity users and tenants of residential property, which are part of non-residential users. Since February 2009, the subsidy scheme has been limited to only residential users. The subsidy has been applied uniformly across the country. From 2008 to 2016, there were a few changes in the conditions of the subsidy measures. In total, there are four phases of the subsidy measure as shown in Table A.2.

Table A.2 Electricity Price Subsidy from 2008

Time periods	Details of electricity price subsidy
August 2008 – January 2009	A residential user *and tenant of residential property* which uses electricity up to 80 kWh per month receives free electricity for that month. A residential user *and tenant of residential property* user which uses electricity more than 80 kWh but not more than 150 kWh per month pays half of its electricity bill for that month.
February 2009 – May 2012	A residential user which uses electricity up to 90 kWh per month and has installed an electricity meter up to 5 amps receives free electricity for that month.
June 2012 – December 2015	A residential user which uses electricity up to 50 kWh per month and has installed an electricity meter up to 5 amps receives free electricity for that month.
January 2016 – present	A residential user which uses electricity up to 50 kWh per month *for at least three consecutive months (including the current month)* and has installed an electricity meter up to 5 amps receives free electricity for that month.

Sources: MEA and PEA

There were a significant number of electricity users who received benefits from the subsidy. In the case of PEA, 74.9% of residential customers received subsidy in August 2008. This includes customers who paid zero and half of their bills. After the conditions were changed in February 2009 and June 2012, the share of those who receive subsidy came down to 61.3% and 22.4%, respectively. For MEA, the share of customers receiving subsidy was considerably lower—only 5.0% in June 2012.[26]

A.2 Calculation of electricity price indexes

In this study, I use three sets of electricity price indexes: residential price index, non-residential price index, and total price index. All sets of price indexes are based on retail prices per kWh including the base tariffs, F_t, and VAT.[27]

[26] The subsidy data for MEA are not available before 2011.
[27] In this study, I do not include the time-of-use (TOU) rates in calculating the electricity tariffs for residential and small general service users. This is because the shares of residential and small general service users who

A.2.1 Residential electricity price index

As discussed earlier, residential electricity tariffs follow a progressive price schedule. Electricity unit costs are therefore different for different levels of electricity consumption. I started the calculation by computing the average residential electricity use per customer per month in each province in 2006. Next, I calculated a median of the provincial consumption per customer in 2006 and used it as a consumption level to calculate the unit price. The median of average provincial consumption in 2006 is calculated to be 108.7 kWh per month. The price index was then obtained by normalizing the unit prices in different years using 2006 as a base year.

For simplicity, I do not take into account the electricity price subsidy when calculating the unit price. The price subsidy does not affect all residential users and data of number of users benefiting from the subsidy are not available for some regions at a certain time. Therefore, it is difficult to estimate how much the subsidy would affect the overall unit price. I instead use four time dummies in the regression to capture the impact of the price subsidy of each phase on electricity consumption.

have chosen to adopt the TOU rates are very small. I use the TOU rates for other types of electricity users because TOU rates are adopted by most of these users (comparing Prachatai, 2016; and MEA, 2018).

A.2.2 Non-residential electricity price index

I first calculated the unit price for each type of non-residential users. I do not include prices for agricultural pumping and temporary services due to the relatively small amount of electricity consumption. As mentioned earlier, for non-residential users, electricity charges vary with voltage levels. I calculated the unit price by using the simple average of prices for all voltage levels because the number of users of each voltage level is not available. The classification of voltage levels in the tariff schedules has remained unchanged and the rates for each voltage level have been adjusted in the same fashion when tariff schedules changed.

After I obtained the unit prices for different groups of non-residential users, I estimated the unit price for the overall non-residential users using weighted average. The weights come from the share of electricity consumption of each group in total non-residential consumption in 2006. Large general service users accounted for the greatest share of 53%, followed by medium general service users with the share of 23%, small general service 13%, and the rests are specific business service and non-profit organization. Similar to the residential electricity price index, I calculate the price index for non-residential users by normalizing the unit prices using 2006 as a base year.

A.2.3 Total electricity price index

The total electricity price index is simply the weighted average of residential and non-residential price indexes. I obtained the weights from the national consumption data in 2006. Figure A1 presents an example of the estimated real electricity price indexes for the BMR from 2006 to 2016. The figure shows that different electricity price indexes are highly correlated with each other.

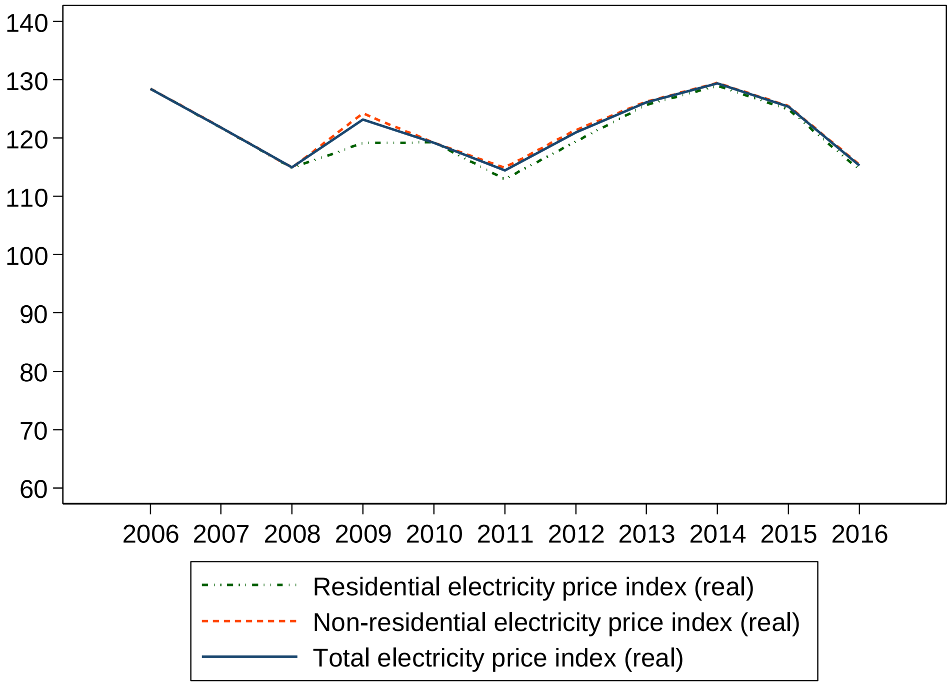

Figure A.1 Residential, non-residential, and total electricity price indexes 2006–2016 for the BMR (real)

Chapter 4

The effects of fuel prices on air quality: Evidence from Bangkok Metropolitan Region[28]

4.1 Chapter overview

Traffic-related air pollution is a serious environmental concern in mega-cities worldwide. This study investigates the causal link between fuel prices and traffic-related air pollution using Bangkok and the surrounding areas as a case study. Bangkok has been ranked being as one of the world's most traffic-congested cities. Daily and monthly data for 1996–2017 are used to model three traffic-related air pollutants: carbon monoxide (CO), nitrogen dioxide (NO_2), and particulate matter with a size of less than or equal to 10 microns in diameter (PM_{10}). Pollution data are collected from 25 monitoring stations. The findings provide evidence that higher fuel prices reduce air pollution from road vehicles. The fuel price elasticities of CO and PM_{10} pollution are found to be around –0.3 to –0.4 and –0.1 to –0.4, respectively. The estimates suggest a fuel price elasticity of NO_2 pollution of –0.2 to –0.3 during 1996–2006. However, the effect of fuel prices on NO_2 after 2006 is positive, potentially due to substitution of gasoline with gaseous fuels. The results imply that abolition of all fuel price subsidies likely helps to reduce air pollution.

4.2 Introduction

The Bangkok Metropolitan Region (BMR), the region covering Bangkok and three adjacent provinces—Nonthaburi, Pathumthani, and Samutprakan—is the centre of Thailand's economy. Although the area accounts for less than 1% of the country's land area, it is the source of 42% of the national gross domestic product (GDP) (Office of the National Economic and Social Development Board, 2018a). Its population in 2015 was 9.2 million, around 14% of Thailand's population. The actual BMR population is, however, likely to be

[28] This research paper has been submitted to Energy Economics and is now under review.

much greater because of unregistered migrants (Bangkok Metropolitan Administration, 2017).

Bangkok has been ranked as being one of the most traffic-congested cities in the world, together with Mexico City, Los Angeles, and Jakarta (INRIX, 2016; Numbeo, 2017; TomTom, 2017). Road traffic is recognized as the major source of air pollution in megacities around the world (Faiz and Sturm, 2002). Particulate matter (PM), nitrogen oxides (NO_x), carbon monoxide (CO), and are among major pollution emitted from road traffic (IEA, 2016b). Vongmahadlek et al. (2009) estimate that, of all emissions over Thailand, road traffic emitted 17% of PM with a size less than or equal to 10 microns in diameter (PM_{10}), 42% of NO_x, and 46% of CO in 2005. The importance of road vehicles as a pollution source is likely greater in Bangkok due to relatively high intensity of road transport and rare incidents of biomass burning compared with other areas in the country.[29]

Figures 4.1–4.3 present the annual mean concentration levels of three traffic-related air pollutants (PM_{10}, nitrogen dioxide (NO_2), and CO) in the BMR from 1996 to 2017. The annual concentrations of PM_{10} and CO show downward trends while the concentration of NO_2 is relatively steady. The levels of PM_{10} and NO_2 are presented with the World Health Organization guideline levels (WHO, 2006) and national standards (Pollution Control Department, 2018a) for annual means. Figure 4.1 shows that PM_{10} concentration exceeded the WHO guideline in all years although it declined to meet the national standard in recent years. NO_2 exceeded the WHO guideline in most years although it always met the national standard (Figure 4.2). For CO, the WHO guideline and national standard for the maximum daily 8-hour means are both set at 9 ppm (WHO, 2013; Pollution Control Department, 2018a). However, the WHO guideline and national standard for annual mean CO is not available. The records show that over 1996–2017, the maximum daily 8-hour means of CO averaged across all stations had been below the standard. However, the measurements at one station exceeded the standard in 2002 and the measurements at some stations almost reached the standard in certain years (Pollution Control Department, 2018a).

[29] According to the estimates of Vongmahadlek et al. (2009), biomass burning contributed to 40% of PM_{10} emissions, 20% of NO_x emissions, and 45% of CO emissions in Thailand in 2005.

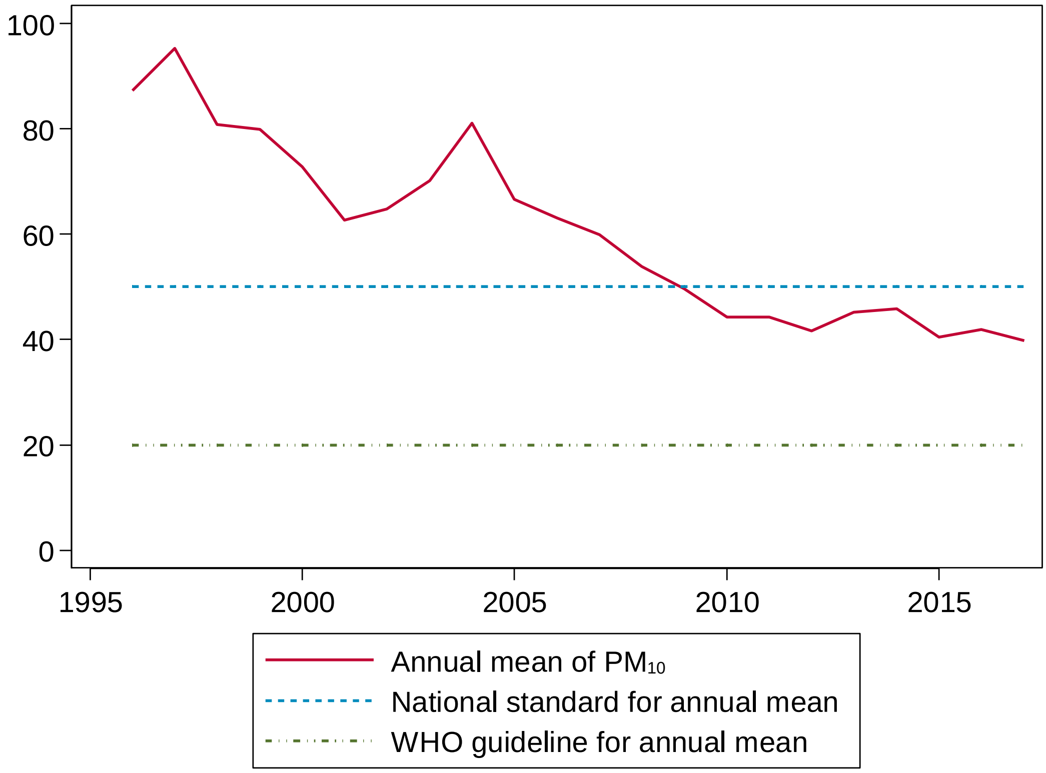

Figure 4.1 Annual average concentration of PM_{10} in the BMR 1996–2017 (μg/m^3)

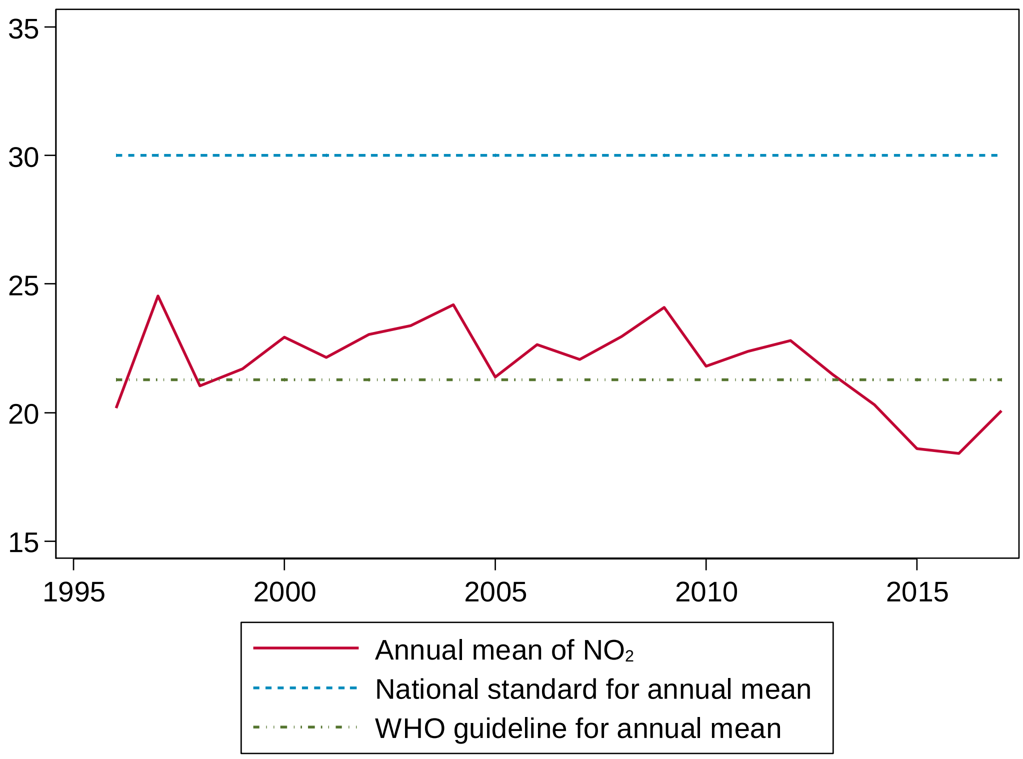

Figure 4.2 Annual average concentration of NO_2 in the BMR 1996–2017 (ppb)

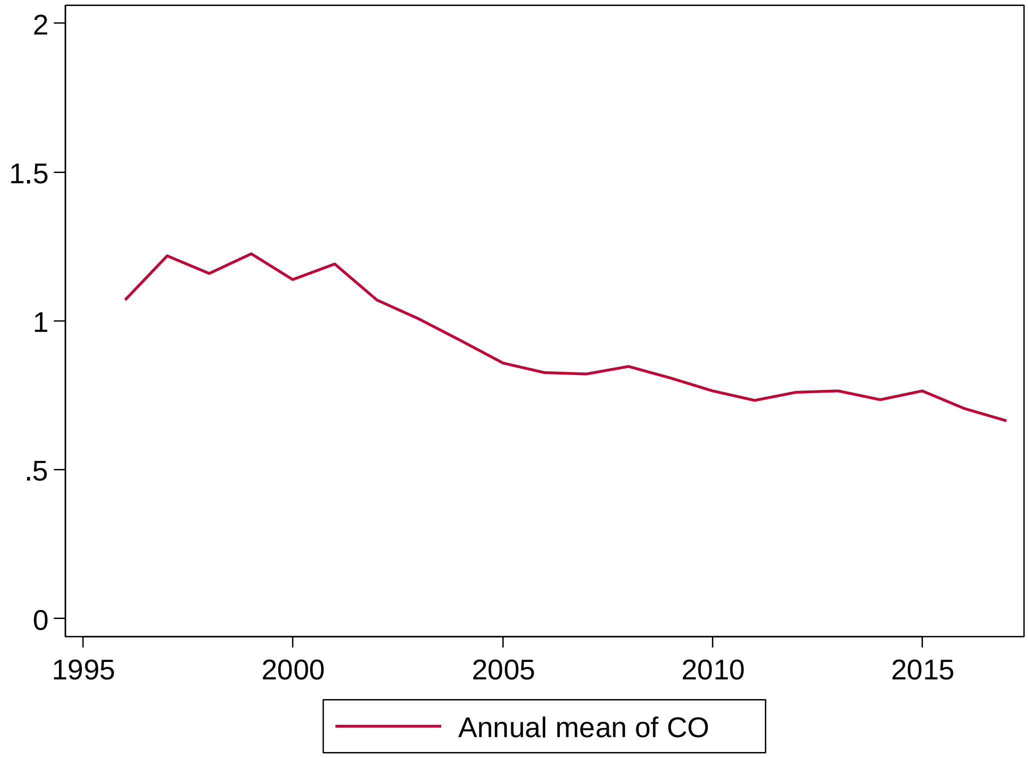

Figure 4.3 Annual average concentration of CO in the BMR 1996–2017 (ppm).

Note: the annual average of pollution levels in Figure 4.1–4.3 are calculated using data from 25 monitoring stations in the BMR obtained from the Department of Pollution Control. For the year 2017, the average is calculated up to 31 October 2017.

A considerable number of studies has shown evidence of the relationship between traffic-related pollution exposure and several adverse health effects. For example, asthma (Andersen et al., 2012; Favarato et al., 2014; Cai et al., 2017;), cardiovascular diseases (Miller et al., 2007; Bell et al. 2009; Brook et al., 2010; Atkinson et al., 2013), lung cancer (Nyberg et al., 2000; Beelen et al., 2008), and adverse birth outcomes and risk to unborn babies of developing health conditions later in life (Brauer et al., 2008; Baïz et al., 2011; van den Hooven et al., 2011). For Thailand, Guo et al. (2015) find that PM_{10}, ozone (O_3), and sulphur dioxide (SO_2) had significant effects on mortality in Thailand during 1999–2008. The World Bank and Institute for Health Metrics and Evaluation (2016) estimate that in 2013 the number of total deaths from air pollution in Thailand was 48,819, with total welfare losses of 6.29% GDP equivalent.

One possible factor that could contribute to changes in air pollution levels is fuel prices. Fuel prices affect the quantity of fuel demanded, which should subsequently have an impact on the amount of pollution emitted from motor vehicles. There is a number of ways in which people may respond to high fuel prices. Some responses tend to reduce air pollution, for example, reducing the distance driven, substituting vehicles with higher rates of fuel consumption with vehicles with lower rates of fuel consumption, taking public transport instead of driving, and moving closer to workplaces. However, substitution between fuels with different chemical compositions may reduce one type of pollution but increase another type of pollution. Fuel prices may also affect other emitters. For example, higher fuel prices may induce a decline in production of some industries, such as petroleum refinery and car production (Lee and Ni, 2002).

As far as I am aware, there are only three published studies attempting to investigate the relationship between fuel prices and traffic-related air pollution directly. The results of these studies, which all look at countries other than Thailand, are fairly inconclusive. Barnett and Knibbs (2014) apply a correlation analysis with daily pollution data from two monitoring stations in Brisbane during 2010 to 2013. They find that an increase in diesel price is associated with a short-term reduction in CO and NO_x, but not PM_{10} and $PM_{2.5}$. On the other hand, changes in gasoline price have no detectable impact on pollution levels. Chen and Lin (2015) employ monthly and annual panel data of seven air pollutants in 19 cities in Taiwan from 1993 to 2011. Their estimates suggest that an increase in fuel price causes a decline in CO, O_3, SO_2, and PM_{10} only after a floating oil pricing mechanism was implemented in Taiwan. The results are insignificant for NO_2, hydrocarbons, and dustfall. Shaw et al. (2018) use weekly data of four air pollutants (CO, NO_2, PM_{10}, $PM_{2.5}$) from four monitoring stations in New Zealand during 2001–2013. Their results suggest that gasoline and diesel prices only have short-term effects on air pollution. Other studies infer the impact of changes in fuel prices on air pollution from estimates of price elasticity of fuel demand, e.g., Sipes and Mendelsohn (2001), Burguillo-Cuesta et al. (2009), and Kim et al. (2011).

This study aims to test the causal effect of fuel prices on the concentration levels of three traffic-related pollutants (CO, NO_2 and PM_{10}) in the BMR. This is the first study to examine the relationship between fuel prices and air pollution in Thailand. The data employed are at the daily and monthly basis from 1996 to 2017. The virtue of the daily data is its high frequency while the monthly estimation allows me to control for other factors likely to impact ambient air pollution such as manufacturing production and overall consumption. The pollution data are collected from 25 monitoring stations across the BMR. Compared with previous studies, data used in this study come from a larger number of pollution measurement points with a longer study period. Also, an instrumental variable (IV) approach is applied to address potential endogeneity in fuel demand. The results show negative and significant fuel price elasticity of CO and PM_{10} for the entire period. Fuel price elasticity of NO_2 is negative and significant in the first half of the study period but changed to positive and significant in the second half. Higher gasoline prices result in a substitution from gasoline to LPG, which releases more NO_2. This might contribute to the positive fuel price elasticity of NO_2 in the second sub-period.

The remainder of this chapter is structured as follows. Section 4.3 provides related background information. Methodology and data are discussed in Section 4.4 and 4.5, respectively. Section 4.6 presents the results. Section 4.7 concludes and discusses policy implications.

4.3 Background Information

4.3.1 Fuel prices in Thailand

The structure of retail fuel prices in Thailand consists of three parts: ex-refinery price, marketing margins, and levies. Since the 1990s, ex-refinery prices and marketing margins have been allowed to be determined by the market. Singapore market prices are used as the reference by Thai refineries to set their ex-refinery prices. This is because Singapore is the major oil trading centre in the region and Singapore oil prices reflect the cheapest possible prices for Thailand to import oil (Boonpramote, 2017). Marketing margins represent distribution costs and profits of the suppliers.

Levies include excise tax, contributions to the oil fund and the energy conservation fund, and value added tax (VAT). To date, the government operates excise tax and an oil fund levy primarily to reduce volatility of retail prices and to cross-subsidize certain fuels

(Boonpramote, 2017). Target maximum prices are set informally by the government. Then, levies are adjusted to keep retail prices below the maximum (Kojima, 2013). If prior-controlled prices are higher than the maximum, the rate of the oil fund levy, and sometimes also the rate of excise tax, are adjusted to be negative (i.e., fuel prices are subsidised). In that case, traders receive payment from the government. Diesel has been one of the most subsidized petroleum products in Thailand (Boonpramote, 2017). From 1996 to 2017, the diesel price was greatly controlled during 2004–2005 and from late 2009 to 2014. Figure 4.4 compares the gasoline price, diesel price, and world crude oil price from 1996 to 2017. The figure shows that the gasoline price correlates highly with the world crude oil price. On the other hand, around 2004–2005 and 2009–2014 the diesel price remains very flat while the gasoline price moved volatilely.

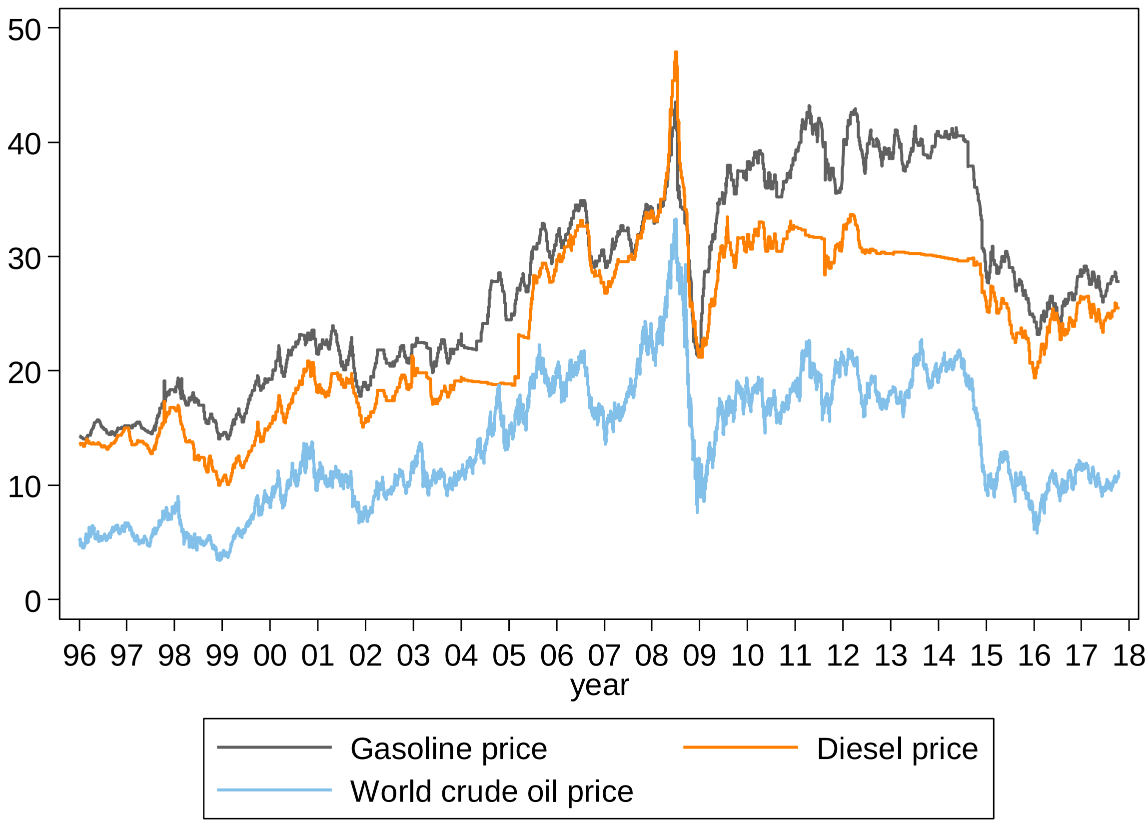

Figure 4.4 Daily retail fuel prices in the BMR and world crude oil price 1996–2017 (real baht/litre). Sources: PTT (2017), the Energy Policy and Planning Office (EPPO, 2017), and the U.S. Energy Information Administration (EIA, 2018). Note: Gasoline price is the average price of gasoline 95, gasohol 95, gasohol 91, and gasohol E20. The world crude oil price is the Western Texas Intermediate

Spot Price FOB converted to Thai baht per litre. Nominal prices are adjusted to real prices using monthly consumer price index for the BMR.

Apart from gasoline and diesel, liquefied petroleum gas (LPG) and compressed natural gas (CNG) are also widely used in automobiles in Thailand. Retail prices of LPG and CNG, however, had been capped with little adjustment. It can be seen from Figure 4.5 that from 2003 to 2017 both prices were very static. Thailand removed price controls on CNG in 2016 and transport LPG in 2017 (The Nation, 2016; Bangkok Post, 2017).

In September 2018, the price control on diesel was reintroduced by capping the domestic retail diesel price at 30 baht per litre (Bangkok Post, 2018). Also, certain types of biofuel blends—such as gasohol E20 and E85—have been substantially cross-subsidized in order to promote the use of biofuels. The cross subsidies was raised in October 2015 causing the price gap between gasohol 95 and E20 to increase from 1.82 to 2.36 baht per litre and the price gap between gasohol 95 and E85 to increase from 4.32 to 6.46 per litre (The Nation, 2015).

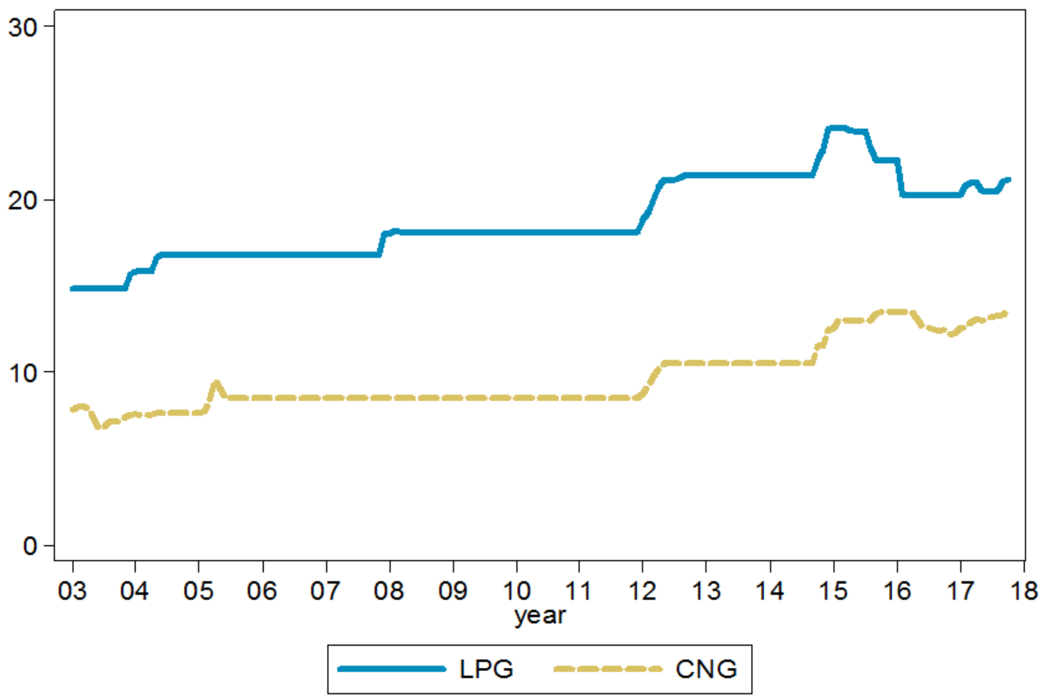

Figure 4.5 Monthly retail LPG and CNG prices for transport in the BMR 2003–2017 (nominal baht/kg). Sources: PTT (2017) and EPPO (2017).

4.3.2 Fuel consumption in the BMR

Figure 4.6 presents the amount of gasoline, diesel, and LPG sold from producers to gas stations each year in the BMR from 2003 to 2017. Sales volume of gasoline and diesel had been fairly stable and not very different from each other. The quantity of gasoline sold was slightly lower than diesel until 2016, when this situation reversed. Sales of LPG, on the other hand, increased remarkably from 2003 to 2013 and then declined in 2015. Notably, LPG consumption increased rapidly when the gasoline price soared or remained at the high level in 2007–2008 and 2010–2013, and decreased when the gasoline price dropped in 2009 and after 2014. Also, the direction of changes in LPG consumption was mostly opposite to the gasoline consumption. This may suggest there was a substantial substitution of LPG for gasoline during the period of high gasoline prices. Substitution between gasoline and LPG is possible because dual-fuel systems can be installed into gasoline cars allowing the vehicles to run on LPG and gasoline alternately. The number of gasoline-LPG vehicles in the BMR was almost 700,000 in 2014 and declined slightly afterwards to around 600,000 in 2017 (Department of Land Transport, 2018). Section 4.6.4 discusses how the gasoline-LPG substitution might affect the gasoline price elasticity of air pollution.

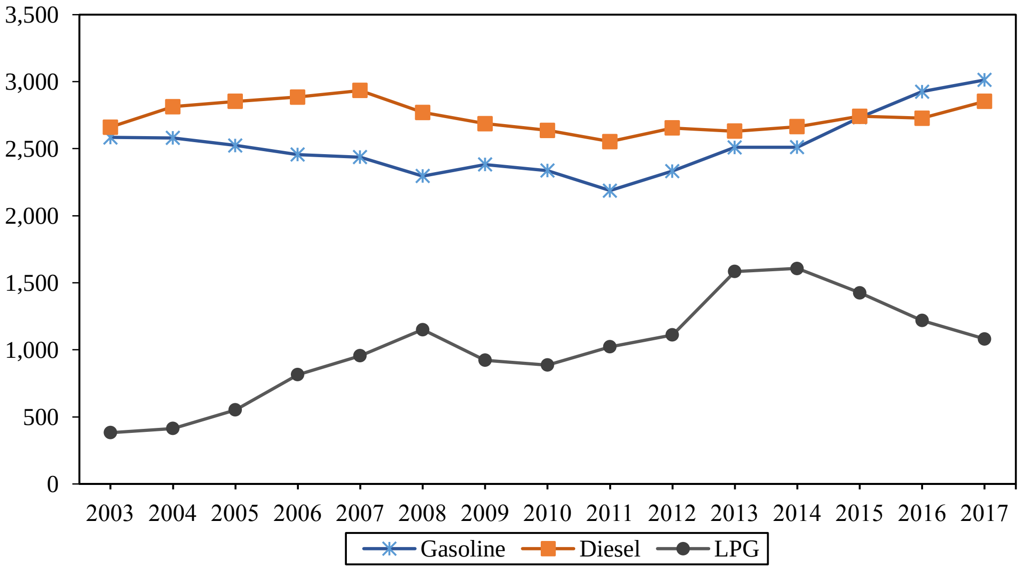

Figure 4.6 Fuels sold from producers to gas stations in the BMR 2003–2017 (million litres per year). Sources: Department of Energy Business (2018). LPG is converted from kilograms to litres using the conversion value of 1 kilogram = 1.96 litres.

Similar to LPG, CNG was also used as a substitute for gasoline. The national data show that CNG sales increased continuously from 2006 to 2014 and declined afterwards (Department of Energy Business, 2018). Nationwide, CNG sales for road transport use was approximately double the transport LPG sales. However, data on CNG consumption by province are not available. In the BMR, almost half of CNG vehicles in 2017 were taxis, buses, and trucks while more than 90 percent of LPG vehicles were private vehicles (Department of Land Transport, 2018). Furthermore, in 2017, the number of vehicles fuelled by LPG in the BMR was 3.5 times higher than the number fuelled by CNG.

4.3.3 Policy measures for controlling air traffic pollution

In Thailand, there are two main types of regulations targeted at reducing air pollution from road traffic. The first is vehicle emissions standards for new and in-use vehicles. For new vehicles, since 1995 Thailand has adopted emission standards from the United Nations Economic Commission for Europe (UNECE) and the European Union (EU). These standards limit the emissions of CO, hydrocarbons (HC), and NO_x from gasoline and light-duty diesel engines. For heavy-duty diesel engines, a limit on PM emissions is also in place. After 1995, these standards were subsequently tightened in 1996, 1997, 1998, 1999, 2001, 2005, and 2013 (Cheewaphongphan et al., 2017; Pollution Control Department, 2018b). The emissions standards for in-use vehicles includes a limit on black smoke for diesel vehicles and a limit on CO and HC for gasoline vehicles. Drivers of vehicles emitting pollutants beyond the in-use vehicle standards are fined and the vehicles are not be allowed to be used until they are repaired and pass a reinspection (Srisurapanon and Wanichapun, 2001).

The second measure concerns fuel quality. The sulfur content in diesel fuel was limited to 0.035% by weight in 2003. The limit was then reduced to 0.005% in 2012. For gasoline, the sulfur limit was reduced from 0.1 to 0.05% in 2003 percent by weight and reduced to 0.005% in 2012. Gasoline is also subjected to an aromatics content standard.[30] The standard was set at 50% by volume in 1994 and reduced to 35 % in 2000 (Pollution Control Department and Bangkok Metropolitan Administration, 2012). Karavalakis et al., (2015) find that aromatics content in gasoline increases CO and PM emissions from vehicles.

[30] Aromatics are hydrocarbon additives to gasoline to raise its octane rating. Benzene, tolune, and xylene are the most common aromatics found in gasoline.

4.4 Methodology

4.4.1 Model specification

I adopt fixed-effects panel regression models applying to daily and monthly data. Fixed effects models allow for controlling area-specific differences in air pollution levels. The model specifications are as follows.

1) Daily estimation

An estimation model of the daily regression for each pollutant has the following form:

$$\mathrm{Ln}A_{i,d} = \alpha_0 + \alpha_1 \mathrm{Ln}P_d + \alpha_2 D_{d:w} + \alpha_3 \mu_{m:y} + \alpha_4 s_i + \boldsymbol{X}'_d \boldsymbol{\varphi} + \varepsilon_{i,d} \qquad (4.1)$$

where i indexes monitoring stations and d indexes day. A is ambient pollution monitored from each monitoring stations. P is the real retail fuel price in baht per litre. I carry out the estimation that uses average fuel price as the price variable, and also the estimation that includes both gasoline price and diesel price. The latter specification allows us to see the effects of potential substitution between gasoline and diesel on air pollution. The coefficient of gasoline price presents the effect of changes in gasoline price on air pollution while holding diesel price (and other control variables) constant, and vice versa.[31] D is a set of 6 day-of-week (*d*:w) dummies. μ is a set of 11 month-of-year (*m*:*y*) dummies. s is a set of station fixed effects. $\boldsymbol{X}$ is a vector of additional control variables consisting of total rainfall in millimetre (mm), log of maximum wind speed in knot, a dummy for wind blowing from the south side (south wind),[32] average temperature in degree Celsius, a public holidays dummy, and a linear time trend. ε is an error term.

Day-of-week dummies are included to take into account the fact that traffic demand varies throughout the week. Month-of-year dummies are introduced to control for remaining seasonal effects in air pollution which could not be captured by the weather and other control

[31] We can also obtain an elasticity for the relative price of gasoline in terms of diesel (γ): $\gamma = \beta_g - \beta_d$ where β_g is the coefficient of the log of gasoline price and β_d is the coefficient of the log of diesel price.

[32] The dummy variable equals to 1 when the wind direction is between 90 and 270 degrees.

variables, e.g., school holidays, and annual festivals and events that are not public holidays but are in the same month every year.[33] A south wind that blows from the direction of the Gulf of Thailand is expected to reduce a greater amount of pollution concentration than an inland wind from the north side. The time trend is included to account for the net impact from factors that change gradually over time, e.g., quality of vehicle engines, quality of fuels, population, number of vehicles, and the expansion of public transport, etc. I also expect the time trend to capture the impact of air pollution controls as outlined in Section 4.3.3 because the control measures have generally been tighten over time. The time trend is also superior to year fixed effects if there existed a delay for the measures to be effective in reducing air pollution.

2) Monthly estimation

The model specification for monthly data is

$$\mathrm{Ln}A_{i,m} = \beta_0 + \beta_1 \mathrm{Ln}P_m + \beta_2 \mu_{m:y} + \beta_3 s_i + \boldsymbol{X'}_m \boldsymbol{\varphi} + \varepsilon_{i,m} \tag{4.2}$$

where m indexes month. In the monthly estimation, fuel price and weather variables are monthly means of the daily data. The monthly regression excludes day-specific dummies but includes the log of manufacturing production index and the log of value added tax (VAT) revenue from all goods and services. The log of manufacturing production index is included to take into account the effects of changes in manufacturing production activities on ambient air pollution. The VAT revenue is used as a proxy for economic conditions. It is likely that the VAT revenue is positively correlated with economic output. An increase in economic output could lead to an increase in fuel consumption and, therefore, air pollution although fuel prices remain unchanged. Another control variable included in the monthly regression is the number of weekend days and holidays in a month.

[33] For example, Loy Krathong, Valentines, and Christmas. Songkran, one of the main festivals, is a public holiday and already captured by the public holidays dummy.

4.4.2 Addressing potential regression problems

1) Potential endogeneity

Coefficients in Equations (4.1) and (4.2) are first estimated using the ordinary least square (OLS) estimator. OLS estimates, however, could be affected by an endogeneity problem because air pollution is associated with demand for fuel. An increase in fuel demand might cause fuel prices to rise, and at the same time lead to an increase in air pollution. This effect could result in a correlation between fuel prices and the error term. To address this potential endogeneity, I also adopt an IV method by instrumenting the log of fuel price (mean price of gasoline and diesel) with log of world oil price converted into baht/litre. The world oil price is an appropriate IV because it is exogenous to the Thai fuel demand but highly correlated with domestic fuel prices. Burke and Nishitateno (2015, 2013), and Burke and Teame (2018) also use the world oil price as an instrument for domestic fuel prices. One downside of this instrument is that it could be correlated with other economic activities (e.g., industrial production) that affect air pollution.

2) Cross-sectional dependence in the error terms

A potential concern of a fixed-effect specification in this case is the cross-sectional (spatial) dependence in the error terms. For example, wind blows pollution from one area to another area, or an increase in economic activities in one area also induces an increase in air pollution in nearby areas causing residuals to be correlated over space. Cross-sectional dependence could cause standard errors to be biased, leading to faulty statistical inference (Driscoll and Kraay, 1998). I performed a Breusch-Pagan Lagrange Multiplier test of independence (Breusch and Pagan, 1980) and Pesaran cross-sectional dependence test (Pesaran, 2004) to test for cross-sectional dependence. The test results suggest that the null of cross-sectional independence must be rejected. Hoechle (2007) recommends the Driscoll and Kraay standard errors (Driscoll and Kraay, 1998) when cross-sectional dependence is present. The Driscoll and Kraay standard errors are also robust to heteroscedasticity and autocorrelation of the moving average type in the error terms (Hoechle, 2007). I employ the

Driscoll and Kraay standard errors in the monthly OLS estimation.[34] The estimate shows that, although the Driscoll and Kraay standard errors are larger, the significance levels of the explanatory variables are similar to using robust standard errors.

4.5 Data

4.5.1 Data sources

Data for the daily estimation cover the period from 6 January 1996 to 31 October 2017. The data for the concentration of three pollutants (CO, NO_2, and PM_{10}) come from 25 monitoring stations across the BMR obtained from the Department of Pollution control. The original data are at the hourly level. I collapse the hourly data into daily data using hourly means. Although the pollution data from the 25 stations provide a large number of observations, the records from each monitoring station contain considerable missing values. Figure 4.7 presents the locations of the 25 monitoring stations. Among the 25 stations, 6 stations are classified as roadside stations by the Department of Pollution control: 48t, 49t, 50t, 52t, 53t, and 54t. However, the figure shows that the rest of the stations are mostly quite close to main roads and are clustered around inner Bangkok. There are two stations, 13t and 16t, located near natural gas power plants. In Section 4.6.3, I show that the results are still robust even when these two stations are excluded.

[34] The sample size of the daily data is beyond the capacity of the software in carrying out the Driscoll and Kraay standard errors. Robust standard errors are instead reported in the daily estimates.

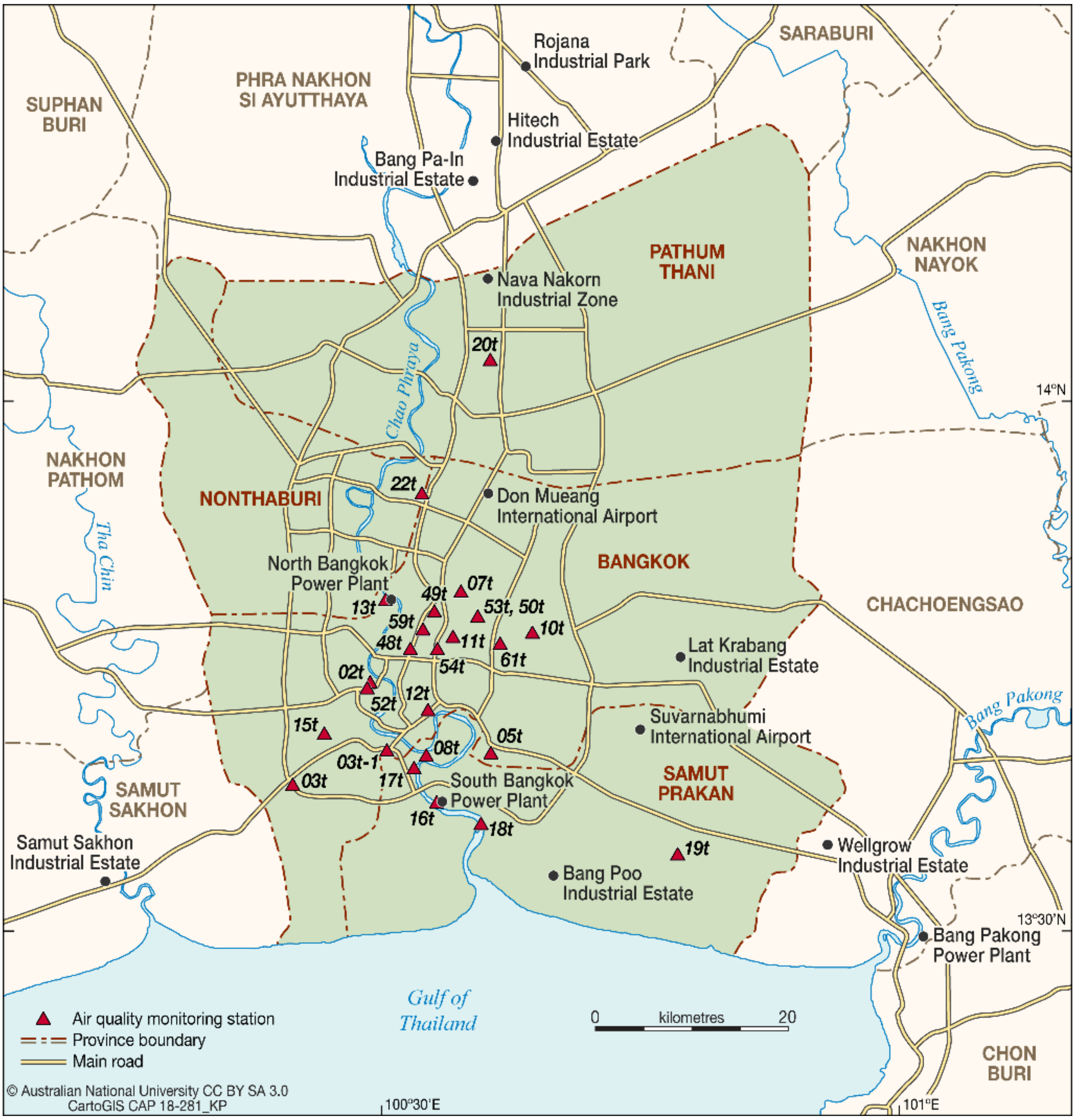

Figure 4.7 Locations of air quality monitoring stations in the BMR

For the fuel price data, I use daily pump prices in the BMR collected from PTT's website (PTT, 2017). PTT is one of the biggest fuel retailers in Thailand. Its website shows that there are more than 200 PTT gas stations in the BMR. All of these stations sell fuel at the same prices. PTT price is preferred because it has the longest record.

The log average fuel price in Equations (4.1) and (4.2) is the log of the simple average between gasoline price and diesel price. The simple average is used because the consumption of gasoline is not very different from the consumption of diesel for road transport as shown in Figure 4.6.

The gasoline price is the simple average price of several gasoline products available in the market at that time: gasoline 95, gasohol 95, gasohol 91, and gasohol E20. I do not, however, include the gasohol E85 price since the price is much lower and less volatile compared with other gasoline fuels. This is because the gasohol E85 price is highly cross-subsidized. Also, gasoline E85 was launched into the market later than other gasoline fuels and the consumption volume has still been relatively modest (Department of Energy Business, 2018).

There was a period, from 3 July 2008 to 31 December 2012, when PTT's price for gasoline 95 is not available. For that period, I use the average gasoline 95 price from other three fuel retailers (Shell, Esso, and Chevron) obtained from the Energy Policy and Planning Office (EPPO, 2017). Fuel prices from all the four companies usually move very closely together. Figure 4.8 shows the movement of gasoline 95 price from the four companies three months before PTT's price became unavailable.

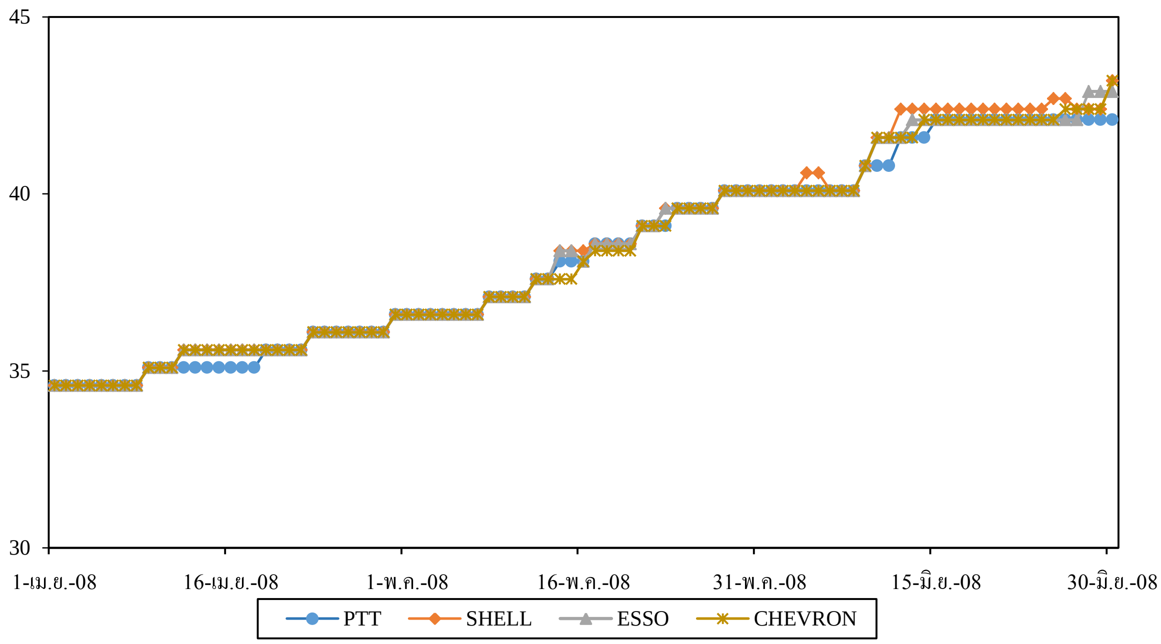

Figure 4.8 Comparison of gasoline 95 price at PTT, Shell, Esso, and Chevron gas stations in the BMR April–June 2008 (baht/litre). Sources: EPPO (2017).

For the IV, world oil price, I use the Western Texas Intermediate Spot Price FOB obtained from website of the U.S. Energy Information Administration (EIA, 2018). Daily exchange rate data from the International Monetary Fund (IMF, 2018) are used to convert the price in US dollar to Thai baht. To adjust nominal fuel prices into real prices, I use the monthly consumer price index for the BMR obtained from the website of the Ministry of Commerce (MOC, 2018). Manufacturing production index and VAT revenue at constant 2003 prices are obtained from the website of the Bank of Thailand (BOT, 2018). Both data are national data.

Weather data are the mean values from several weather stations across the BMR. Data are obtained from the Thai Meteorological Department. Rainfall and temperature are collected from 8 weather stations while wind speed is collected from 4 weather stations, subject to data availability. For wind direction, I use only the weather station situated closest to the centre of the BMR as the representative.

4.5.2 Unit root testing

I carried out two unit root tests on the log of pollution (average across 25 stations), fuel price, and weather variables with linear time trend. The first test is the augmented Dickey-Fuller test (ADF test – Dickey and Fuller, 1979) by choosing the optimal lag length based on Schwarz’s Bayesian information criterion (SBIC). The second test is the Phillips-Perron test (Phillips and Perron, 1988). Both tests suggest that the null of a unit root can be rejected for the log of pollution and weather variables. The test results for deseasonalised pollution series—the residuals from the regressions of pollution on month-of-year dummies and weather variables—also suggest that the series are stationary except for the ADF test of deseasonalised log PM_{10}. For the log of fuel price, both tests were unable to reject the nulls of unit roots in levels but were able to reject in first differences. However, when regressing each of the log pollution on log fuel price, I get a stationary residual, which tends to suggest that the pollution and the fuel price series have the same order of integration.

It is possible that the noisy nature of pollution data might conceal the random walk characteristics and lead to a Type 1 error in the unit root tests. Figure 4.9–4.11 show the monthly plots of pollution data, both unadjusted and deseasonalised series. It is shown that although the deseasonalised series are smoother but still very noisy. Hall and Qaqeesh (2009) find that the size of distortion for Dickey-Fuller test increases with the variance of noise and sample size. Therefore, I carried out further investigations by performing a Johansen test for cointegration (Johansen, 1988). The results show that there is one cointegrating vector between the log of fuel price and each of the pollutant. This suggests that the log of fuel price and each of the pollutant are cointegrated and they all have unit roots. In this case, a first different specification will be misspecified because it excludes the long-run relationships among the cointegrated variables (Enders, 2014). Also, when the series are cointegrated, OLS in levels is superconsistent: OLS estimates converge to the true values (as sample gets larger) faster than in the I(0) case (Stock, 1987).

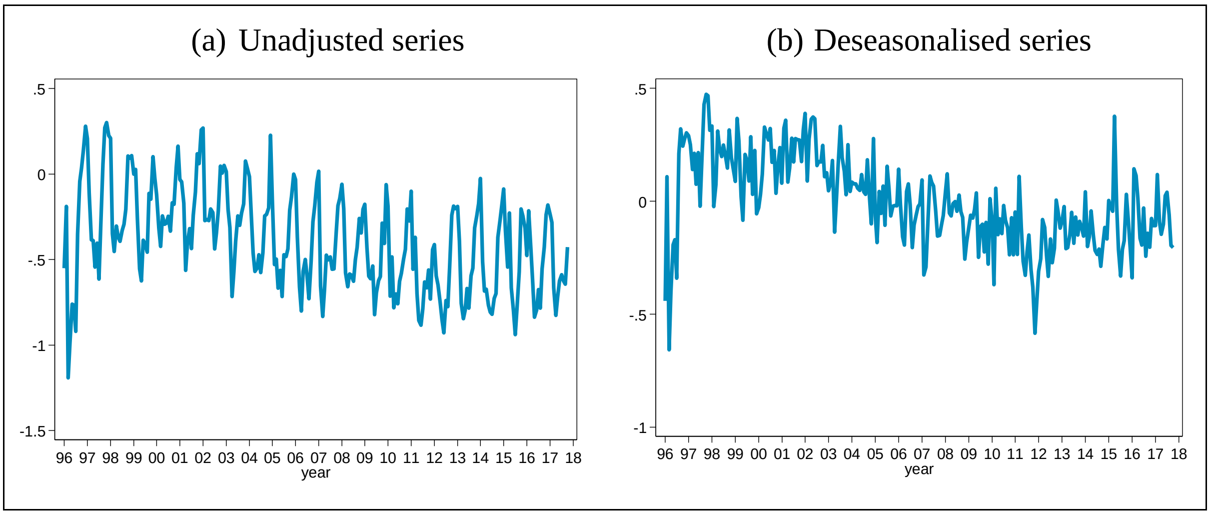

Figure 4.9 Monthly plots of logs of CO (ppm)

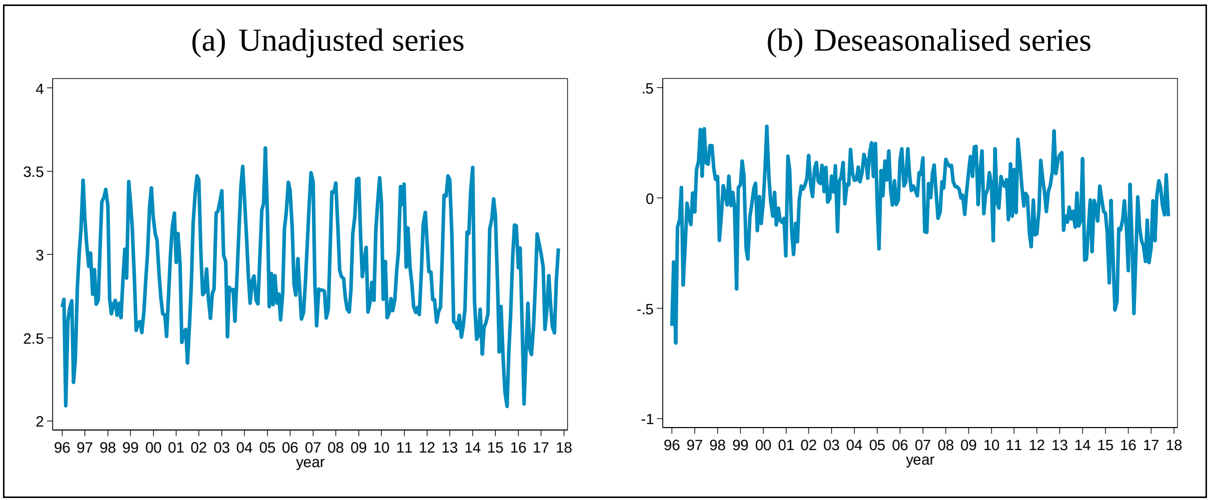

Figure 4.10 Monthly plots of logs of NO_2 (ppb)

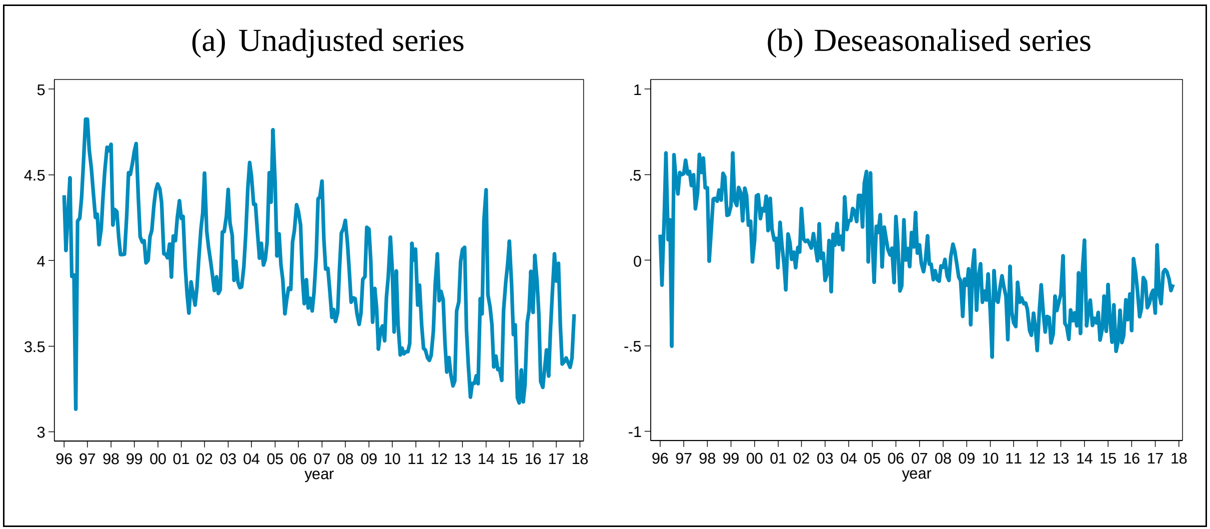

Figure 4.11 Monthly plots of logs of PM_{10} ($\mu g/m^3$)

Note: The unadjusted series are the simple average of log pollution across stations from the monthly data. The deseasonalised series are obtained from the residuals from the regressions of log pollution on 11 month-of-year dummies and weather variables.

4.6 Results

4.6.1 Daily estimates

The results of daily estimates for the three pollutants are presented in Table 4.1. For each pollutant, there are three columns of estimates: OLS with the log of average fuel price, OLS with the log of gasoline price and the log of diesel price, and IV where the log of average fuel price is instrumented with the log of world oil price. The IV-related statistics suggest that the instrument is strong: the coefficient on the instrument in the first-stage regression is positive and highly significant as expected, and the *F* statistic on the instrument is very large.

For the estimates with the log of average fuel price, OLS and IV give fairly similar price elasticities, suggesting that endogeneity issues do not appear to be major. The estimated fuel price elasticities are negative and significant as expected for CO and PM_{10}. However, the estimated fuel price elasticities of NO_2 are positive and significant. In Section 4.6.4, I show that this is not the case for all sub-periods and discuss what could contribute to the positive price elasticity of NO_2. The OLS and IV estimates suggest that a 10% increase in average fuel price will induce a 2.6–2.7% decrease in CO concentration and a 0.9–1.4% in PM_{10} concentration in the ambient air.

The results of the models that include gasoline and diesel prices show that if diesel price remains constant, a 10% increase in gasoline price will result in a reduction of 3.1% in CO concentration and 1.8% in PM_{10} concentration. However, if gasoline price remains constant, a change in diesel price will not have a significant effect on air pollution. The estimates could imply that drivers are likely to substitute diesel for gasoline when gasoline price increases, but are unlikely to substitute gasoline for diesel when diesel price increases, all else being equal. For example, gasoline car drivers are able to switch to cars, mini-vans, or pickup trucks fuelled with diesel to avoid higher fuel costs when gasoline price increases. On the other hand, buses and trucks are normally fuelled with diesel; gasoline buses or trucks are rare. The results might also suggest that the own price elasticity of diesel consumption is smaller than that of gasoline consumption.

For other coefficients, the estimates show that a stronger wind and wind blowing from the south will lessen air pollution. Higher temperature is also associated with lower air pollution. Rainfall, on the other hand, tends to reduce the intensity of PM_{10} but not the other two pollutants. This might be because rain affects particulate pollution but not gaseous pollution. Overall, air pollution subsides by 8–17% on public holidays. Similar findings are found for weekend days (not shown). The coefficients of time trend indicate a declining trend of all pollutants by 0.004–0.01% per day, *ceteris paribus*.

4.6.2 Monthly estimates

Table 4.2 shows monthly estimates. The estimated fuel price elasticities from both OLS and IV specifications are fairly similar to the daily estimates. However, the point estimates of fuel price elasticities of PM_{10} are slightly larger and the coefficient of the log gasoline price for PM_{10} is insignificant. The weather coefficients are comparable to the daily estimation. The coefficients of the log of manufacturing production index are positive and significant for all pollutants. On the other hand, the coefficients of the log of VAT revenue are negative and significant for CO. This is presumably due to high consumption spending during long holidays where many people in the BMR travel to other parts of the country, leaving the roads in the BMR relatively uncrowded. The difference in number of holidays and weekend days in a month does not have a significant effect on the concentration of the pollutants. The coefficients for the time trend are still negative and significant.

Table 4.3 presents the OLS estimates of the monthly data where additional control variables are included. The first additional control variable is the log of total electricity consumption in the BMR. This variable is meant to be a proxy for the electricity production from the BMR power plants that could affect pollution levels, especially NO_2. Emissions from natural gas power plants contain more NO_x than CO and PM (Krittayakasem et al., 2011). The second additional control variable is the log of average price between LPG and CNG. The estimation periods are subjected to the data availability of the additional control variables: 2002–2017 for the models with the electricity consumption variable and 2003–2017 for the models with the gaseous fuel price variable.

It should be noted that because the estimations associated with the results in Table 4.1 and 4.2 are cointegration analyses (as discussed in Section 4.5.2), the estimates provide long-run relationships rather than day-to-day or month-to-month responses. That is, the results do not suggest that an increase in fuel prices will reduce air pollution in the next day or month. Instead, the effects tend to emerge in the long run when drivers have fully adjusted their behaviours to the higher fuel prices, such as changing their cars to more fuel-efficient ones or relocating to shorten the driving distance or to get access to public transport.

With the two additional control variables, the fuel price elasticities of air pollution in Table 4.3 are still very similar to the main estimates in Table 4.2. The coefficients of the electricity consumption variable are positive for NO_2 but insignificant. The negative and significant coefficient of the electricity consumption variable for CO in column (2) might be explained by people spending more time at home and less time driving, meaning that electricity consumption increases but CO emissions sourced from traffic decrease. The inclusion of the electricity consumption variable affects the coefficients of the manufacturing production index and VAT revenue significantly, likely because these three variables are highly correlated. The coefficients of gaseous fuel price are only significant for CO. The positive signs make sense: higher gaseous fuel price leads to larger consumption of gasoline, which is the key source of CO pollution.

Table 4.1 Main estimates from daily data 1996–2017

Dependent variable: Ln level of pollution$_{i,d}$	CO (ppm)			NO_2 (ppb)			PM_{10} (μg/m^3)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV
Ln Average fuel price$_d$ (real baht/litre)	–0.27*** (0.01)		–0.26*** (0.01)	0.29*** (0.01)		0.32*** (0.01)	–0.14*** (0.01)		–0.09*** (0.01)
Ln Gasoline price$_d$ (real baht/litre)		–0.31*** (0.02)			0.26*** (0.02)			–0.18*** (0.01)	
Ln Diesel price$_d$ (real baht/litre)		0.03 (0.02)			0.04 (0.01)			0.03 (0.01)	
Ln Highest wind speed$_d$ (knot)	–0.47*** (0.01)	–0.46*** (0.01)	–0.47*** (0.01)	–0.45*** (0.01)	–0.45*** (0.01)	–0.45*** (0.01)	–0.34*** (0.01)	–0.33*** (0.01)	–0.34*** (0.01)
South wind$_d$	–0.11*** (0.004)	–0.11*** (0.004)	–0.11*** (0.004)	–0.14*** (0.003)	–0.14*** (0.003)	–0.14*** (0.003)	–0.11*** (0.002)	–0.11*** (0.003)	–0.11*** (0.003)
Mean temperature$_d$ (Celsius)	–0.04*** (0.001)	–0.04*** (0.001)	–0.04*** (0.001)	–0.06*** (0.001)	–0.06*** (0.001)	–0.06*** (0.001)	–0.02*** (0.001)	–0.02*** (0.001)	–0.02*** (0.001)
Rainfall$_d$ (mm)	0.004*** (0.0002)	0.004*** (0.0002)	0.004*** (0.0002)	0.003*** (0.0002)	0.003*** (0.0002)	0.003*** (0.0001)	–0.001*** (0.0001)	–0.001*** (0.0002)	–0.001** (0.0002)
Public holiday$_d$	–0.17*** (0.01)	–0.17*** (0.01)	–0.17*** (0.01)	–0.16*** (0.01)	–0.16*** (0.01)	–0.16*** (0.01)	–0.08*** (0.01)	–0.08*** (0.01)	–0.08*** (0.01)
Day-of-week dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-of-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend$_d$	–0.00004*** (–0.000001)	–0.00004*** (–0.000001)	–0.00004*** (–0.000001)	–0.0001*** (–0.000003)	–0.0001*** (–0.000001)	–0.0001*** (–0.000001)	–0.0001*** (0.000001)	–0.0001*** (0.000001)	–0.0001*** (0.000001)
R^2	0.46	0.46	0.46	0.43	0.43	0.43	0.48	0.48	0.48
Observations	131,276	131,276	131,276	133,126	131,276	133,126	130,145	130,145	130,145
Instrumented variable: Ln Average fuel price$_d$ (real baht/litre). Instrument: Ln World oil price$_d$ (real baht/litre)									
Coefficient on instrument			0.50***			0.49***			0.50***
F statistic on instrument			906,929			929,048			949,696

Note: *,**,*** represent significance level at 10%, 5%, and 1%, respectively. Coefficients on constant, month-of-year dummies and station fixed effects not reported. Robust standard errors in parenthesis. R^2 includes explanatory variable of station fixed effects.

Table 4.2 Main estimates from monthly data 1996–2017

Dependent variable: Ln level of pollution$_{i,m}$	**CO (ppm)**			**NO_2 (ppb)**			**PM_{10} (μg/m^3)**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	IV	OLS	OLS	IV	OLS	OLS	IV
Ln Average fuel price$_m$ (real baht/litre)	–0.38***		–0.36***	0.21***		0.24***	–0.37***		–0.35***
	(0.09)		(0.06)	(0.04)		(0.05)	(0.06)		(0.03)
Ln Gasoline price$_m$ (real baht/litre)		–0.36***			0.23*			–0.25	
		(0.13)			(0.12)			(0.16)	
Ln Diesel price$_m$ (real baht/litre)		–0.03			–0.02			–0.13	
		(0.10)			(0.12)			(0.15)	
Ln Wind speed$_m$ (knot)	–0.49***	–0.47***	–0.50***	–0.26**	–0.27**	–0.27***	–0.23**	0.23*	–0.24***
	(0.11)	(0.09)	(0.09)	(0.11)	(0.11)	(0.07)	(0.12)	(0.12)	(0.07)
Temperature$_m$ (Celsius)	–0.04***	–0.04***	–0.04***	–0.04***	–0.04***	–0.04***	–0.03	–0.03	–0.03***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Ln Rainfall$_m$ (mm)	0.003	0.003	0.003	0.01*	0.01*	0.01***	–0.01**	–0.01**	–0.01***
	(0.004)	(0.004)	(0.004)	(0.01)	(0.01)	(0.003)	(0.01)	(0.01)	(0.003)
Ln Manufacturing production index$_m$	0.46**	0.45**	0.43***	0.25*	0.27*	0.22**	0.52***	0.52***	0.49***
	(0.18)	(0.18)	(0.11)	(0.14)	(0.15)	(0.09)	(0.14)	(0.14)	(0.07)
Ln VAT revenue (real million baht)$_m$	–0.28**	–0.29**	–0.28***	–0.09	–0.08	–0.09	0.11	0.11	0.11
	(0.12)	(0.12)	(0.09)	(0.13)	(0.13)	(0.08)	(0.12)	(0.12)	(0.07)
Number of holidays and weekend days$_m$	0.001	0.001	0.0004	–0.004	–0.004	–0.005	–0.001	–0.001	–0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Month-of-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time trend$_m$	–0.001***	–0.001***	–0.001***	–0.002***	–0.002***	–0.002***	–0.006***	–0.005***	–0.005***
	(0.0005)	(0.0005)	(0.0004)	(0.0003)	(0.001)	(0.0003)	(0.0006)	(0.0006)	(0.0003)
R^2	0.60	0.60	0.60	0.53	0.53	0.53	0.61	0.61	0.61
Observations	4,617	4,617	4,617	4,701	4,701	4,701	4,611	4,611	4,611
Instrumented variable: Ln Average fuel price$_d$ (real baht/litre). Instrument: Ln World oil price$_d$ (real baht/litre)									
Coefficient on instrument			0.46***			0.47***			0.48***
F statistic on instrument			15,077			14,028			16,870

Note: *,**,*** represent significance level at 10%, 5%, and 1%, respectively. Coefficients on constant, month-of-year dummies and station fixed effects not reported. Standard errors in parenthesis. The Driscoll & Kraay standard errors are presented for the OLS estimates to address the cross-sectional dependence in the residuals. The Driscoll & Kraay standard errors are also robust to heteroscedasticity and autocorrelation of the moving average type in the error terms. Robust standard errors are presented for the IV estimates. R^2 includes explanatory power of station fixed effects.

Table 4.3 OLS estimates from monthly data with more control variables

Dependent variable: Ln level of pollution$_{i,m}$	**CO (ppm)**		**NO_2 (ppb)**		**PM_{10} (µg/m^3)**	
	(1)	(2)	(3)	(4)	(5)	(6)
Ln Average fuel price$_m$ (real baht/litre)	–0.43***	–0.31*	0.22***	0.34***	–0.43***	–0.37***
	(0.12)	(0.17)	(0.07)	(0.09)	(0.08)	(0.10)
Ln Wind speed$_m$ (knot)	–0.50***	–0.40***	–0.43***	–0.45***	–0.33**	–0.41***
	(0.13)	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)
Temperature$_m$ (Celsius)	–0.02	–0.01	–0.09***	–0.09***	–0.05**	–0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Ln Rainfall$_m$ (mm)	0.003	0.005	0.01	0.01**	–0.01*	–0.01*
	(0.004)	(0.004)	(0.01)	(0.006)	(0.01)	(0.01)
Ln Manufacturing production index$_m$	0.67***	0.89***	–0.21	–0.23	0.32**	0.32*
	(0.24)	(0.22)	(0.16)	(0.17)	(0.15)	(0.17)
Ln VAT revenue (real million baht)$_m$	–0.20	–0.10	0.05	–0.07	0.44**	0.32*
	(0.17)	(0.19)	(0.15)	(0.17)	(0.19)	(0.17)
Number of holidays and weekend days$_m$	–0.003	0.001	–0.01	–0.01	–0.01	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Month-of-year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Station fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time trend$_m$	–0.0005	–0.0001	–0.003***	–0.003***	–0.006***	–0.01***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Additional control variables:						
Ln Electricity use (Gigawatt-hour)$_m$	–0.75	–1.09*	0.65	0.65	–0.13	–0.37
	(0.67)	(0.61)	(0.40)	(0.43)	(0.40)	(0.38)
Ln Average price of automotive LPG and CNG (real baht/kg)$_m$		0.51**		0.35		0.27
		(0.24)		(0.22)		(0.21)
R^2	0.59	0.59	0.60	0.59	0.62	0.63
Observations	3,321	3,086	3,393	3,152	3,375	3,140
Time periods	2002–2017	2003–2017	2002–2017	2003–2017	2002–2017	2003–2017

Note: *,**,*** represent significance level at 10%, 5%, and 1%, respectively. Coefficients on constant, month-of-year dummies and station fixed effects not reported. Standard errors in parenthesis. The Driscoll & Kraay standard errors are presented for the OLS estimates to address the cross-sectional dependence in the residuals. Robust standard errors are presented for the IV estimates. R^2 includes explanatory power of station fixed effects.

4.6.3 Robustness check

1) Time series estimation

To first check the robustness of the main results, I apply time series estimation instead of fixed effects. The demeaned time series, rather than raw time series, are employed to reduce the effects of missing values in pollution data.[35] The formula for demeaned time series of log of pollution ($\tilde{A}_d$) is provided in Equation (4.3). I first take the sample mean of the log pollution for monitoring station *i* over the entire period. To calculate the demeaned values, the sample mean is subtracted from the log of pollution at station *i* at time d. $\tilde{A}_d$ is derived from the cross-sectional averages of all the demeaned values:

$$\tilde{A}_d = \frac{\sum_{i=1}^{n}(\text{Ln}A_{i,d} - \overline{\text{Ln}A_i})}{n} \quad \text{where} \quad \overline{\text{Ln}A_i} = \frac{\sum_{d=1}^{k}\text{Ln}A_{i,d}}{k} \tag{4.3}$$

Finally, the time series of $\tilde{A}_d$ is used to estimate the coefficients.

The results of demeaned time series estimation from daily and monthly data are presented in Tables 4.3 and 4.4. The daily estimation provides similar results to the fixed-effects estimates. The fuel price elasticity of CO is around –0.3, NO_2 around 0.3, and PM_{10} around –0.1 to –0.2. The monthly estimation gives slightly different results. The fuel price elasticities of NO_2 are still positive but become insignificant. The fuel price elasticity of PM_{10} in the OLS estimation is negative and significant but the IV estimation gives an insignificant coefficient.

[35] With missing data, the mean pollution in a time series model could be significantly distorted when data from stations on the high side (i.e., stations in the inner city) or the low side (i.e., stations in the outer city) become missing.

Table 4.4 Estimates of the demeaned time series 1996–2017

Dependent variable: Level of pollution$_d$ (log demeaned)	CO (ppm)		NO_2 (ppb)		PM_{10} (μg/m^3)	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Daily estimates:						
Ln Average fuel price$_d$ (real baht/litre)	–0.27*** (0.02)	–0.27*** (0.02)	0.30*** (0.02)	0.32*** (0.02)	–0.15*** (0.02)	–0.11*** (0.02)
R^2	0.50	0.50	0.57	0.57	0.59	0.59
Observations	7,968	7,968	7,968	7,968	7,948	7,948
Monthly estimates:						
Ln Average fuel price$_m$ (real baht/litre)	–0.28*** (0.09)	–0.27*** (0.10)	0.07 (0.07)	0.13 (0.09)	–0.18** (0.08)	–0.14 (0.09)
R^2	0.79	0.79	0.81	0.81	0.81	0.81
Observations	262	262	262	262	262	262

Note: Robust standard errors in parenthesis. *,**,*** represent significance level at 10%, 5%, and 1%, respectively. The same control variables as Table 4.1 and Table 4.2 are included in the daily and monthly estimation, respectively, except for the station fixed effects.

2) Excluding some monitoring stations

Next, I perform another robustness check by excluding some monitoring stations from the estimation. Columns (1)–(3) in Table 4.5 present the estimated fuel price coefficients where two stations near the power plants (13t and 16t in Figure 4.7) are excluded. Columns (4)–(6) present the estimates where only the six roadside stations are included. The coefficients are estimated using OLS because the IV estimates do not reveal a major endogeneity issue. The results in columns (1)–(3) are quite close to the main estimates. For columns (4)–(6), the results are similar overall except that the fuel price elasticity of CO from the daily estimation is smaller. However, coefficient estimated from the monthly regression is still very close to the main estimates.

Table 4.5 Panel estimates excluding some monitoring stations 1996–2017

Dependent variable: Level of pollution$_d$ (log demeaned)	Exclude two stations near the power plants			Include only six roadside stations		
	(1)	(2)	(3)	(4)	(5)	(6)
	CO	NO_2	PM_{10}	CO	NO_2	PM_{10}
Daily estimates:						
Ln Average fuel price$_d$ (real baht/litre)	–0.29*** (0.01)	0.29*** (0.01)	–0.14*** (0.01)	–0.03** (0.01)	0.32*** (0.02)	–0.21*** (0.01)
R^2	0.46	0.44	0.49	0.31	0.45	0.50
Observations	121,410	119,498	116,660	35,300	21,933	35,038
Monthly estimates:						
Ln Average fuel price$_m$ (real baht/litre)	–0.42*** (0.06)	0.22*** (0.04)	–0.37*** (0.03)	–0.28*** (0.06)	0.40*** (0.15)	–0.45*** (0.06)
R^2	0.60	0.53	0.62	0.47	0.53	0.62
Observations	4,274	4,223	4,140	1,240	767	1,256

Note: Robust standard errors in parenthesis. *,**,*** represent significance level at 10%, 5%, and 1%, respectively. The same control variables as Table 4.1 and Table 4.2 are included in the daily and monthly estimation, respectively. R^2 includes explanatory power of station fixed effects.

4.6.4 Sub-period analysis and potential effects of gasoline-LPG substitution

In this section, I divide the entire study period into two sub-periods, each sub-period has eleven years: 1996–2006 and 2007–2017. The estimated price coefficients are presented in Table 4.6. The most noticeable difference between the two sub–periods is that the price coefficients for NO_2 change from negative and significant over 1996–2006 to positive and significant over 2007–2017. Smaller point estimates are observed for CO in the first sub-period. For PM_{10}, the point estimates are slightly larger in the first sub-period. The choice of splitting sample, instead of introducing interaction terms, is supported by the large sample size and the less restrictive model setting.

Table 4.6 Comparison of fuel price elasticities during 1996–2006 and 2007–2017

Dependent variable: Level of pollution$_d$	CO (ppm)		NO_2 (ppb)		PM_{10} (μg/m^3)	
	(1)	(2)	(3)	(4)	(5)	(6)
	1996–2006	2007–2017	1996–2006	2007–2017	1996–2006	2007–2017
Daily estimates:						
Ln Average fuel price$_d$	–0.05*	–0.16***	–0.21***	0.22***	–0.27***	–0.12***
(real baht/litre)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
R^2	0.48	0.46	0.45	0.47	0.44	0.45
Observations	59,532	71,744	65,948	67,178	57,546	72,599
Monthly estimates:						
Ln Average fuel price$_m$	–0.09	–0.29***	–0.26***	0.28***	–0.48***	–0.22***
(real baht/litre)	(0.09)	(0.08)	(0.08)	(0.06)	(0.07)	(0.05)
R^2	0.64	0.60	0.57	0.57	0.58	0.61
Observations	2,101	2,516	2,335	2,366	2,022	2,589

Note: Robust standard errors in parenthesis. *,**,*** represent significance level at 10%, 5%, and 1%, respectively. The same control variables as Table 4.1 and Table 4.2 are included in the daily and monthly estimation, respectively. R^2 includes explanatory power of station fixed effects.

As discussed in Section 4.3.2, there was a considerable substitution of gasoline with LPG between the late 2000s and early 2010s when the gasoline price was relatively high. LPG vehicles are found to release more NO_x but less CO and PM than gasoline vehicles (for NO_x and CO: Murillo et al., 2005; Yang et al., 2007; Darade and Dalu, 2013; Kerbachi et al., 2017; for PM: Ristovski et al., 2005; Yang et al., 2007; Myung et al., 2012).[36] The higher combustion temperature of LPG (900–1000°C) compared with gasoline (500–800°C) is one factor contributing to the higher NO_x emissions (Yang et al., 2007). Therefore, a switch from gasoline to LPG when gasoline price rises could result in an increase in NO_2. It is noteworthy to mention that a large amount of NO_2 emissions are released from a petrochemical industrial complex not far from the BMR (Tunlathorntham and Thepanondh, 2017). The higher demand for transport LPG from the gasoline-LPG substitution might also induce an increase in LPG production that resulted in higher NO_2 emissions. On the other hand, the substitution is expected to cause a larger reduction in CO and PM_{10} when gasoline price increases, compared with the case where LPG is not an option. The results, however, suggest differently

[36] CNG vehicles are also found to emit more NO_x but less CO and PM compared to gasoline vehicles (Aslam et al., 2006; Dondero and Goldemberg, 2005; Jahirul et al., 2010; and Tabar et al., 2017).

for PM_{10}. The use of diesel particle filter (DPF) in modern diesel vehicles, which helps reduce PM_{10} emissions (Platt et al., 2017), might contribute to the reduction in the responsiveness of PM_{10} pollution to the changes in fuel prices in the second sub-period.

Table 4.7 presents the coefficient estimates of a model for automotive LPG and CNG sales estimated using monthly data. LPG sales are total sales in the BMR while CNG sales are total across Thailand due to data availability. The models are estimated using a first difference specification which provides estimates for a short-run relationship.[37] The results confirm that LPG is a substitute for gasoline—higher gasoline price leads to higher LPG demand—with a cross-price elasticity of 0.2. The own-price elasticity is insignificant. However, the estimates do not show a significant effect of gasoline price on CNG consumption.

Table 4.8 shows the results of how the uses of gasoline and automotive LPG affect air pollution differently. The results suggest that when LPG consumption is held constant, a 10% increase in gasoline consumption will lead to a 3% and 5% increase in CO and PM_{10} pollution, respectively. However, an increase in gasoline consumption does not have a significant effect on NO_2 pollution. On the other hand, when gasoline consumption is held constant, a 10% increase in LPG consumption will result in a 1% increase in NO_2 pollution but have no significant effects on CO and PM_{10} pollution.

[37] The reasons for adopting a first-difference specification are as follows. The unit root tests suggest that the dependent variable and three of the explanatory variables—the logs of the real gasoline price, real LPG price, and VAT revenue—are nonstationary at their levels but stationary at first differences. As suggested by the ADF test, the residual of the level regression is nonstationary. The Johansen cointegaration test suggests that the dependent variable is cointegrated with the log real gasoline price, but not with the log real LPG price and log VAT revenue variables. These test results imply that the model in levels might not be appropriate.

Table 4.7 Automotive LPG and CNG demand: Monthly estimates 2007–2017

Dependent variable: Δ Ln Sales of automotive …	LPG (1)	CNG (2)
Δ Ln Gasoline price$_m$ (real baht/litre)	0.22* (0.11)	0.14 (0.11)
Δ Ln LPG price$_m$ (real baht/kg)	–0.07 (0.23)	0.35 (0.30)
Δ Ln CNG price$_m$ (real baht/kg)	–0.27 (0.26)	–0.74** (0.32)
Δ Ln VAT revenue$_m$ (real million baht)	0.29* (0.17)	0.17 (0.11)
Δ Number of holidays and weekend days$_m$	0.002 (0.003)	–0.005** (0.003)
Δ Temperature$_m$ (Celsius)	–0.001 (0.01)	0.003 (0.01)
Δ Rainfall$_m$ (mm)	–0.001 (0.002)	–0.002 (0.002)
Δ Ln Newly registered vehicles$_m$	0.04 (0.05)	0.04 (0.03)
Flood	–0.23*** (0.06)	–0.12*** (0.03)
Month-of-year dummies	Yes	Yes
R^2	0.59	0.43
Observations	129	129

Note: Δ denotes a first difference operator. Robust standard errors in parenthesis. *,**,*** represent significance level at 10%, 5%, and 1%, respectively. Automotive LPG sales are LPG sold from producers to gas stations in the BMR in thousand kilograms obtained from the Department of Energy Business. Automotive CNG sales are CNG sold to gas stations across Thailand in million cubic feet per day obtained from EPPO. LPG price is the retail price for LPG used for transport in the BMR obtained from EPPO. CNG price is the retail pump price for the BMR obtained from PTT. Nominal prices are adjusted to real prices using monthly consumer price index for the BMR. Newly registered vehicles are numbers of all types of vehicles newly registered in the BMR in that month, obtained from the Department of Land Transport. Flood is a dummy variable for October and November 2011.

Table 4.8 Effects of fuel sales on air pollution: Monthly estimates 2007–2017

Dependent variable: Ln level of pollution$_m$	CO (ppm)	NO_2 (ppb)	PM_{10} (µg/m^3)
	(1)	(2)	(3)
Ln Gasoline sales$_m$ (thousand litres)	0.29** (0.13)	0.04 (0.13)	0.46*** (0.10)
Ln LPG sales$_m$ (thousand litres)	0.06 (0.05)	0.09* (0.05)	0.01 (0.04)
R^2	0.61	0.59	0.61
Observations	2,139	2,120	2,196

Note: Robust standard errors in parenthesis. *,**,*** represent significance level at 10%, 5%, and 1%, respectively. Gasoline and LPG sales are the amounts sold from producers to gas stations in the BMR. The same control variables as Table 4.2 are included in the estimation except for the log of VAT revenue because the fuel sales variables likely capture the effects of changes in the consumption level already.

4.6.5 Comparison between directly estimated and implied elasticities

Instead of estimating fuel price elasticity of air pollution directly from the fuel price and air pollution data as previously shown, it is also possible to calculate implied elasticities by estimating price elasticities of fuel consumption and multiply with the coefficients in Table 4.8. The estimated price elasticities of fuel consumption for the period 2007–2017 are shown in Table 4.9. The price elasticity for gasoline plus diesel is estimated to be –0.32. Columns (2) and (3) present the estimates for gasoline and diesel separately. Consistent to what expected in Section 4.6.1, gasoline is more price elastic than diesel. The estimated price elasticities of fuel consumption in Table 4.9 are in the range of long-run price elasticities estimated by previous studies: from –0.2 to –0.8 (Goodwin et al., 2004; Brons et al., 2008; Lin and Prince, 2013; and Coglianese et al., 2017).

Table 4.9 Price elasticities of fuel consumption: Monthly estimates 2007–2017

Dependent variable: Ln Sales of …	Gasoline + Diesel	Gasoline	Diesel
	(1)	(2)	(3)
Ln Average fuel price$_m$ (real baht/litre)	–0.32*** (0.02)		
Ln Gasoline price$_m$ (real baht/litre)		–0.48*** (0.03)	
Ln Diesel price$_m$ (real baht/litre)			–0.08** (0.03)
R^2	0.79	0.50	0.77
Observations	130	130	130

Note: Robust standard errors in parenthesis. *,**,*** represent significance level at 10%, 5%, and 1%, respectively. Average fuel price is a simple average of gasoline and diesel prices. Fuel sales are the amounts sold from producers to gas stations in the BMR. The control variables include number of newly registered vehicles and month-of-year dummies, and flood dummy (a dummy variable for October and November 2011).

In Table 4.10, I calculate the implied elasticities by multiplying the coefficients from Table 4.8 and from column (1) in Table 4.9, and compare the results with the monthly estimates for the same period from Table 4.6. It is shown that the implied elasticities are smaller . One reason that could explain the difference in the direct and implied elasticities is the fact that the implied elasticity is estimated from the amount of fuels sold to gas stations. The data cannot capture other channels of fuel sales such as wholesale purchases directly from fuel producers, and fuels used in transporting fuels from producers to gas stations. If these are included, the coefficients in Table 8 tend to be larger as more pollution sources are combined. In addition, the difference in the elasticities might also be due to the heterogeneity in estimation methods and model specifications.

Table 4.10 Comparison between directly estimated and implied elasticities 2007–2017

Pollutants	Directly estimated elasticities (From Table 4.6)	Implied elasticities (Derived from Table 4.8 and 4.9)
	(1)	(2)
CO	–0.29	0.29 × (–0.32) = –0.09
NO_2	0.28	0.04× (–0.32) = 0.01
PM_{10}	–0.22	0.46 × (–0.32) = –0.15

Note: The directly estimated elasticities are monthly estimates from Table 4.6 for the period 2007–2017. The implied elasticities are multiplication of the coefficients from Table 4.8 and from column (1) in Table 4.9.

4.7 Conclusion and policy implications

Bangkok and its surrounding areas have for years been confronted with air pollution problem largely sourced from high traffic density. This study has investigated the effects of fuel prices on three traffic-related air pollutants (CO, NO_2, and PM_{10}) using daily and monthly data from 1996 to 2017. The estimates for the entire study period suggest that the fuel price elasticity of CO is around –0.3 to –0.4. The fuel price elasticity of PM_{10} is around –0.1 to –0.4. The estimated price elasticity of NO_2 is positive. Nevertheless, when the study period is divided into two sub-periods, the price elasticity of NO_2 is found to be positive only in the second sub-period (after 2006). In the first sub-period, the estimated price elasticity of NO_2 is negative and significant at around –0.2 to –0.3. The substitution of gasoline with LPG is a potential factor causing the price elasticity of NO_2 to change after 2006, as higher gasoline prices lead to more LPG consumption and LPG have more NO_2 emissions than gasoline. The results tend to provide long-run estimates rather than day-to-day or month-to-moth responses.

The estimated fuel price elasticities of air pollution are similar to those that have been found for the price elasticities of road traffic and fuel consumption. The demand for road traffic and fuels are found to be price inelastic. The long-run price elasticities are estimated to be around –0.2 to –0.8 (Goodwin et al., 2004; Graham and Glaister, 2004; Brons et al., 2008; Lin and Prince, 2013; and Coglianese et al., 2017).

The results show that air pollution in the BMR is on a diminishing trend, probably due largely to the tightened pollution control measures and improving engine quality. However, the results imply that the diesel subsidy during 2009–2014 likely slowed down the alleviation of the pollution problem. Also, the gas price controls that resulted in a switch from gasoline to gaseous fuels over the same period might increase NO_2 pollution. Furthermore, the fall in fuel prices from late 2014 to 2017 likely exacerbated the pollution problem.

The findings support the case that the adoption of price-based measures such as pollution charges (BBC, 2017) tend to work effectively in reducing air pollution. Road pricing might also be helpful. Percoco (2013) and Gibson & Carnovale (2015) find that road pricing in Milan, Italy, reduces the concentration of air pollutants. Another policy measure that should be implemented simultaneously with price-based tools is facilitating a switch from cars to public transport, e.g., by enhancing the quality of service and extending the coverage of network.

Currently, less than 0.3% of vehicles in Thailand run on electric power—both pure electric and hybrid electric vehicles (Department of Land Transport, 2018). In the future, when electric vehicles become a viable mainstream option, the overall emissions from transport will decline and the connection between fuel prices and traffic pollution will weaken. However, this study provides a hint of how traffic demand in the BMR will likely respond to changes in the costs of electric power.

Although price controls on CNG and LPG were recently removed, the price control on diesel is still employed periodically, especially when fuel prices are high. The government usually argues that the diesel price control will help to reduce the impact of increasing fuel prices on consumers (Reuters, 2018). Although fuel subsidies may assist in keeping the cost of living low, it is shown that fuel subsidies are inefficient policy measures for helping poor households because the subsidies provide more benefits to higher income households since the rich consume more fuels, directly and indirectly, than the poor. (Arze del Granado et al., 2012). On the other hand, fiscal gains from subsidy reform offer large potential for reducing other taxes and implementing policies targeting the poor (Coady et al., 2017). The results from this study show that eliminating subsidies of all fuels will reduce air pollution and likely accelerate the transition from fossil fuel vehicles to vehicles powered by electricity or other clean energy sources.

Chapter 5

Conclusion

5.1 Summary of findings

This thesis has investigated three different issues regarding energy use and environmental impacts in Thailand as presented in Chapter 2–4. In Chapter 2, I apply a multiregional input-output model and structural decomposition analysis (SDA) to investigate the role of international trade in Thailand's energy-related CO_2 emissions and factors contributed to changes in the emissions over the period 1990 to 2010. CO_2 emissions from both production-based and consumption-based accounting are examined. The findings suggest that on average, emissions embodied in exports accounted for around 46% of Thailand's production-based emissions, while only around 27% of the consumption-based emissions came from imports. This confirms that Thailand is a net CO_2 exporter. The SDA results show that CO_2 emissions increased largely due to the growth in per capita consumption. Although energy efficiency gains helped to reduce emissions growth significantly, the effect was only around half of the effect of growing per capita consumption.

Chapter 3 provides a study about electricity demand in Thailand. The study investigates GDP elasticity of electricity demand using provincial data from 2006 to 2016. The results show that the GDP elasticities of residential, non-residential, and total electricity demand decline with GDP levels. This applies to both short-run and long-run estimates. In the long-run, the non-residential demand is found to be income elastic with the GDP elasticity around 1.4–1.5 whereas the residential demand is income inelastic with the GDP elasticity around 0.6–1.7. The long-run GDP elasticity for total electricity demand is around 1.1–1.2.

In Chapter 4, I examine the effects of fuel prices on ambient air pollution in the Bangkok Metropolitan Region (BMR). Both daily and monthly data from 1996 to 2017 are used in the analysis. I find that an increase in fuel prices will lead to a decrease in air pollution. A 10% increase in fuel prices tends to reduce concentration of CO by around 3–4% and PM_{10} by around 1–4%. The estimates show evidence that a 10% increase in fuel prices reduced NO_2 pollution by around 2–3% over the first of the study period, from 1996 to 2006. For the period after 2006, I get a positive fuel price elasticity of NO_2. I show that the positive fuel price elasticity of NO_2 is likely to be a result of a substitution of gasoline with LPG, the fuel that releases more NO_2, in road vehicles.

5.2 Policy implications

The findings in this thesis provide useful policy recommendations concerning energy and environmental management in Thailand in three main areas.

5.2.1 Climate policy

The findings in Chapter 2 imply that to slow down the rising trend of carbon dioxide emissions and ensure that Thailand will achieve the national emissions target in 2030, climate policy in Thailand needs to be strengthened tremendously. Policies to improve energy efficiency alone will not be sufficient. Achieving the national emissions target will require an energy transformation to clean energy sources, especially in the two largest emitting sectors: the electricity and transport sectors.

Not only is renewable energy more environmentally friendly, it is also likely to be more cost-effective in the near future. Over the past few decades, the costs of solar and wind power have declined substantially. It is estimated that by 2020, electricity produced from renewable energy will be cheaper than energy from fossil fuels (International Renewable Energy Agency, 2018). In addition, due to the declining costs of battery, electric cars may be cheaper than their petroleum counterparts by 2025 (Hodges, 2018). However, as the electricity market in Thailand is a near-monopoly and highly regulated market, an energy transition may not occur spontaneously once the costs of renewable energy become lower than fossil fuels. Introducing a wholesale electricity market that supports fair competition and allowing the electricity price to be determined by temporal electricity generation costs and temporal demand are among the necessary conditions to accommodate high levels of renewable energy penetration (Goggin et al., 2018).

5.2.2 Electricity forecasting and infrastructure planning

The study in Chapter 3 provides implications about electricity forecasting. It is important to produce precise electricity demand forecasts because electricity demand forecasts inform investment decisions about electricity generation as well as power transmission and distribution system (Steinbuks et al., 2017). The results shows that electricity demand tends to grow more slowly as GDP rises. This suggests that that electricity forecasting should apply a smaller GDP elasticity as the economy grows. Furthermore, a smaller GDP elasticity should be applied in richer provinces. I show that, given the same economic growth rate, the difference of the implied electricity demand growth rates between high-income and low-income provinces could be as large as 2%.

Although the estimates show that electricity demand is highly correlated with GDP, electricity forecasters should also consider other factors potentially affecting future electricity demand such as new investments in industrial and service sectors, demographic changes, and technological transitions in energy use. In particular, the electrification of road transport will increase demand for electricity. However, the use of rooftop solar will reduce electricity demand from the grid.

5.2.3 Fuel pricing policy

According to the findings in Chapter 4, abolishing fuel price subsidies or increasing fuel taxes tends to help reduce air pollution in the BMR. This should also apply to other dense urban areas where traffic is the main source of air pollution. However, care must be taken to use fuel pricing policies to tackle air pollution problem because changes in fuel prices are associated with several economic and social impacts (International Monetary Fund, 2008; Lin and Jiang, 2011). Another caveat is that the estimates in Chapter 4 are based on cointegration analysis, which provides long-term effects. Therefore, increasing fuel prices might not effectively reduce air pollution within a short time frame.

Nevertheless, it is important that the costs of environmental impacts such as air pollution are taken into account when designing fuel pricing policies. Economic theory suggests that socially optimal prices must incorporate their externalities or associated side effects, which are not normally reflected in market prices due to market failure. Apart from local air pollution, emissions from traffic also contain CO_2, which has climate impacts. Furthermore, fuel prices are also related to traffic congestion (Burke et al., 2017) and number of road deaths (Burke and Nishitateno, 2015; Burke and Teame, 2018). Although fuel prices must likely be higher to account for externalities, the government can reduce the household burden by reducing income or consumption taxes in response to higher fuel taxes (Parry et al., 2014).

5.3 Implications for future research

This thesis offers a number of interesting avenues for future research. First, Thailand has recently executed a voluntary emission trading scheme (ETS) as a pilot scheme and has planned to establish a more broad-based ETS in the future (Usapein and Chavalparit, 2017). As the findings in Chapter 2 point out that a large portion of Thailand's CO_2 emissions are embodied in Thai exports, this would mean that ETS is likely to have a significant impact on Thai exports by making the products become more expensive. Hübler et al. (2014) show that in the case of China, ETS will result in a considerable lost in net exports. Consequently, it would be useful to explore design options for ETS that could mitigate the impact on export competitiveness.

Second, in Chapter 3, due to the lack of electricity subsidy data, I chose to calculate the electricity price variable from the tariff schedules. This causes the calculated price does not have variation between provinces. As a result, the estimation cannot take into account the progressive structure of the electricity tariff in Thailand. As discussed in Chapter 3, the progressive electricity pricing could be one reason contributing to the declining electricity-GDP elasticity. Therefore, if future research is able to employ an electricity price variable that varies with consumption quantity, the estimation could provide less unambiguous results.

Finally, the air pollution in Bangkok has recently become critical as the air quality index in central Bangkok area has reached an unhealthy level and hundreds of schools were shut (Chuwiruch, 2019). One of the main pollutants causing the issue is $PM_{2.5}$ (The Straits Times, 2019). The study in Chapter 4 does not include $PM_{2.5}$ because the available data are very limited. Up to 2017, $PM_{2.5}$ concentration had been measured at only four monitoring stations and the data from each station had been collected for less than five years. In the future, if $PM_{2.5}$ data become more extensive, it would be interesting to see whether $PM_{2.5}$ concentration is affected by fuel prices and how the results compare to other pollutants. Another potential extension when the use of electric vehicles becomes more widespread is to include the share of electric vehicles as one control variable. The results can also suggest to what extent electric vehicles are helpful for air pollution reduction.

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