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Reducing Carbon Emissions by Phasing Out Fossil Fuel Subsidies
Empirical Evidence from the Philippines

David Alexander Huber (41877)

Abstract: Eliminating subsidies on fossil fuels is widely recognized as one of the most important steps in the fight against climate change. While fossil fuel subsidies have received increasing attention in research, there is little to no empirical evidence confirming the theoretical emission reduction potential of phasing out such subsidies. The present thesis aims to fill this gap and answer the question, whether phasing out fossil fuel subsidies on petroleum products reduces greenhouse gas emissions from transport at the real-world example of the 1996 fossil fuel subsidy reform in the Philippines. To this end, I construct a synthetic Philippines from a pool of comparable donor countries, where the fossil fuel subsidy reform did not occur. I then compare emissions from transport in the actual Philippines to this hypothetical counterfactual to isolate the effect of the reform from other confounding factors. The results suggest that nine years after the reform, emissions were 26% lower compared to the scenario where fossil fuel subsidies persisted. In absolute terms, the elimination of fossil fuel subsidies reduced emissions by more than 33 million tons of CO_2 equivalent between 1996 and 2004. The results are statistically significant at the 1% level and robust to all standard robustness tests from the synthetic control literature. The present thesis complements the mostly theoretical modeling literature by providing some first ex-post empirical evidence that phasing out fossil fuel subsidies substantially reduces greenhouse gas emissions.

Keywords: Fossil Fuel Subsidies, Emissions, Synthetic Control, Carbon Pricing, Philippines

JEL: H23, L91, Q41, Q54, Q58

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Table of Contents

List of Figures

List of Tables

List of Abbreviations

ASEAN Association of Southeast Asian Nations
DID Difference in Differences Method
DOE Department of Energy
EDGAR Emissions Database for Global Atmospheric Research
GHG Greenhouse Gas
GST Goods and Service Tax
IEA International Energy Association
IMF International Monetary Fund
IPCC Intergovernmental Panel on Climate Change
LOO Leave-One-Out
MSPE Mean Squared Prediction Error
OECD Organisation for Economic Co-Operation and Development
OPSF Oil Price Stabilization Fund
PPP Purchasing-Power-Parity
RMSPE Root Mean Squared Prediction Error
SAARC South Asian Association for Regional Cooperation
SDG Sustainable Development Goal
VAT Value Added Tax
WTO World Trade Organization

1 Introduction

Limiting global warming to 1.5°C by the end of the century requires immediate and rapid large-scale reductions in greenhouse gas (GHG) emissions (UNEP, 2021). In the Paris Climate Agreement, each country stated the "nationally determined contributions" it will take to reduce its carbon emissions (UNEP, n.d.).[1] With this bottom-up approach, the main burden in the fight against climate change lies on the national mitigation policies of each country (Andersson, 2019). While the vast majority of economists agree that a carbon-tax would be the most efficient and cost-effective measure to achieve a reduction in emissions (The Wall Street Journal, 2019), subsidizing the extraction and consumption of fossil fuels still is a widely used policy all around the world. According to estimates by the International Monetary Fund (IMF), global subsidies to fossil fuels amounted to USD 450 billion in 2020 (Parry et al., 2021). Already three decades ago, Larsen and Shah (1992) argued that any policy aimed at reducing emissions should first and foremost eliminate fossil fuel subsidies. Today, studies estimate that reforming fossil fuel subsidies would reduce worldwide GHG emissions by up to 10 percent by 2030 (Global Subsidies Initiative, 2019). Therefore, phasing out fossil fuel subsidies is widely recognized as one of the most important steps if countries want to meet their commitments under the Paris Climate Agreement and is included in the United Nation's Sustainable Development Goals (SDG) under target 12.c (UNEP, 2019). However, reforming fossil fuel subsidies is very difficult for social and political reasons and only few countries have managed to do so successfully (Rentschler & Bazilian, 2017). Consequently, there is also little to no empirical evidence confirming the theoretical emission reduction potential of phasing out fossil fuel subsidies in an ex-post study. This is unfortunate considering the global pervasiveness of fossil fuel subsidies and their potentially big contribution to tackling climate change.

In the present thesis, I aim to answer the question, *whether phasing out subsidies on petroleum products reduces GHG emissions* and present some first ex-post empirical evidence on the emission reduction potential from phasing out fossil fuel subsidies by studying the example of the Philippine transport sector. Between 1985 and 1997, the Philippine government subsidized domestic oil prices with more than USD 1.1 billion[2] in today's currency through an Oil Price Stabilization Fund (OPSF), which lead to additional GHG emissions of 400'000 tons of CO_2 equivalent annually[3] (Beltran, 2011). The OPSF was abolished as part of the deregulation of the downstream oil sector between 1996 and 1998 (U, 2000). Thereafter, prices were fully market-determined and strongly increased

[1] For simplicity, the term carbon emissions is used as a synonym for GHG emissions henceforth.

[2] Author's own conversion to today's currency based on data from Beltran (2011) and Mendoza (2014), using consumer price indices from the World Bank (2022a).

[3] Assuming a conversion rate of nitrogen oxide to CO_2 of 298 (Eurostat, 2022).

as a result of a combination of rising international oil prices, currency depreciation and the abolishment of the OPSF. The econometric challenge at hand is to disentangle the effect of the 1996 fossil fuel subsidy reform on fuel prices and consumption from these other external shocks and the underlying macroeconomic trends. I solve this challenge by constructing a synthetic counterfactual from a pool of donor countries that mimics the Philippines in all aspects, but where the 1996 reform did not take place. By comparing GHG emissions from transport in the synthetic Philippines with the GHG emissions in the actual Philippines, I am able to filter out the emission reduction caused by the 1996 fossil fuel subsidy reform from all other factors. My results suggest that due to the elimination of fossil fuel subsidies, per capita emissions from transport were 16% lower four years after the reform and 26% lower nine years after the reform, compared to the scenario were subsidies persisted. In absolute terms, the elimination of fossil fuel subsidies in the Philippines cumulatively saved a total of 33 million tons of CO_2 equivalent over the nine posttreatment periods. The results are statistically significant at the 1% level and robust to all standard robustness tests from the synthetic control literature.

The present thesis contributes to the literature in several dimensions. First of all, to the best of my knowledge, the present thesis is the first study to provide causal empirical evidence of a reduction in GHG emissions stemming from phasing out fossil fuel subsidies. While several studies estimated the emission reduction potential of eliminating fossil fuel subsidies theoretically (Burniaux & Chateau, 2014; Chepeliev & van der Mensbrugghe, 2020), there is little to no research documenting this empirically (Global Subsidies Initiative, 2019; Solarin & Al-Mulali, 2021). Given the great political-economical complexity of the issue and the numerous potential counteracting factors, it is of great importance to verify the theoretical emission reduction potential of eliminating fossil fuel subsidies in a real-life setting. The present thesis provides some first empirical results to fill this gap. Second, by exploiting the fact that a subsidy is nothing else than a negative tax, the present thesis builds methodologically on a related stream of research using the synthetic control method to study emission reductions in connection to carbon taxation (See e.g., Andersson (2019), Runst and Höhle (2022) or Leroutier (2022)). In this sense, the present study benefits from the recent experiences using synthetic controls in the literature on carbon taxation and expands the use of the methodology to a new field of research. Lastly, considering that fossil fuel subsidies are still a widespread policy, the experience from the Philippines might be of relevance for many other countries aiming to reduce their GHG emissions to meet their nationally determined contributions under the Paris Climate Accord.

The rest of the paper is organized as follows. Chapter 2 provides the necessary background on fossil fuel subsidies and their reform in the Philippines. Subsequently, Chapter 3 provides a brief overview of the relevant literature on carbon taxation and fossil fuel subsidies. Chapters 4 and 5 describe the methodology and data used in the present thesis. Chapter 6 presents the results of the empirical estimation, which are then discussed in Chapter 7. Lastly, the main findings are summarized in Chapter 8.

2 Background

This chapter provides the necessary background on the fossil fuel subsidy reform in the Philippines for the present analysis. The first section briefly defines fossil fuel subsidies for the purpose of this thesis. The subsequent section provides a timeline of important events leading up to the subsidy reform in 1996 and provides the necessary political context. The last section discusses the impact of the fossil fuel reform on domestic fuel prices in more detail. This section also investigates the link between the fossil fuel reform and a reduction in GHG emissions from the transport sector.

2.1 Fossil Fuel Subsidies

This section briefly describes and defines fossil fuel subsidies as necessary for the present thesis. A longer discussion on the definition, scope and, measurement of fossil fuels can be found in Appendices A.1 - A.3.

Defining fossil fuel subsidies is not a straightforward task (Sovacool, 2017). Fossil fuel subsidies can come in various forms and there is no consensus on their definition, scope and, measurement (UNEP, 2019). For the purpose of the present thesis, I choose to follow the approach applied by the Organization for Economic Co-Operation and Development (OECD, 2005) and the International Energy Association (IEA, 2014) and define fossil fuel subsidies as any government support that keeps consumer energy prices below market levels or increases profits for producers by lowering production costs or increasing received prices above market levels. While some might argue that this definition is too limited and underestimates fossil fuel subsidies because it fails to internalize their full social cost, it is the most commonly used definition in the international debate surrounding fossil fuel subsidies (Parry et al., 2021).

2.2 Political and Historical Context

This chapter provides the necessary political and historical context surrounding the 1996 petroleum price liberalization in the Philippines. More specifically, this chapter discusses the effects of an Oil Price Stabilization Fund in the setting of fuel prices and to what extent it constituted a fossil fuel subsidy.

The Philippines have a small but very limited domestic oil production and rely almost entirely on imports to meet domestic demand (Mendoza, 2014). This dependence exposes the country to changes in international oil prices and the depreciation of the local currency. In order to attenuate this vulnerability, the Philippine government created a so-called Oil Price Stabilization Fund (OPSF) in 1984 (Beaton et al., 2013). Before the inception of the OPSF, prices of petroleum products were largely market-determined (U, 2000).

The idea behind the OPSF was that it would act as a buffer against shocks in international petroleum prices and exchange rate swings (Bernardo & Tang, 2008). When world oil prices were high, the fund would subsidize petroleum products; when world oil prices were low the fund would be replenished through special levies (Beaton et al., 2013). Oil price stabilization funds are a widely used policy tool. Other countries which have implemented such funds are Vietnam, Gabon, Malawi, Chile, Colombia, and Peru (Kojima, 2016). However, stabilization funds tend to deplete quickly in times of prolonged high oil prices, just when they are needed the most, leaving countries with serious fiscal deficits (Kojima, 2016). In these scenarios, stabilization funds end up acting as a direct government subsidy to petroleum prices (U, 2008). Kojima and Koplow (2015) explicitly state that budgetary transfers to oil price stabilization funds are to be considered as fossil fuel subsidies under the definition of the OECD. Overall, there is mounting evidence that the costs of stabilization funds far outweigh their benefits and ever more countries move away from using them (Kojima, 2016).

The Philippine OPSF was no exemption from this. During the initial years, domestic prices were fixed once or twice a year by the state, guaranteeing industry players a full recovery of costs plus a decent margin, with the OPSF absorbing changes in world oil prices and exchange rate fluctuations (Mendoza, 2014). The fund started running into trouble in 1989 and the government was forced to provide fiscal assistance to keep it alive (Bernardo & Tang, 2008). By 1995, the fund was once more strapped for cash and the government could no longer afford to keep it running (Mendoza, 2014). In March 1996, the first Downstream Oil Industry Regulation act was passed and entered into force in May of the same year. The act removed price controls and marked the beginning of the end of the OPSF (Aldaba, 2003). Initially, the fund was kept in place to moderate prices during the transition phase to full price liberalization (Mendoza, 2014). However, the deregulation act was declared unconstitutional one year later due to some anti-competitive provisions and in February 1998, a second, more comprehensive deregulation act was signed into law (Bernardo & Tang, 2008). With the new deregulation law, all outstanding debts of the OPSF were transferred to the government budget and the fund was officially abolished (Mendoza, 2014). Prices of petroleum products quickly rose to international levels and fluctuated with market movements (Beaton et al., 2013). Since then, the deregulation of the downstream oil industry has been challenged repeatedly and has been examined by three independent oil price reviewing committees in 2005 (IOPRC), 2008 (U) and 2012 (IOPRC); each of them confirming the current policy of market-based pricing and advocating against the re-establishment of an OPSF. The most important events surrounding the establishment of the OPSF and the deregulation of the downstream oil industry are summarized in Table 1. For simplicity, the reform period from 1996 until 1998 including both reform attempts is referred to as the 1996 reform hereafter.

Table 1: Timeline OPSF and Subsidy Reform in the Philippines

Year	Event
October 1984	Establishment of the OPSF
March 1996	First reform attempt passed
May 1996	First reform enters into force
November 1997	First reform declared unconstitutional
February 1998	Second reform attempt passed
March 1998	Full price liberalization, abolition of the OPSF

Note: Author's own elaboration based on Aldaba (2003), Bernardo and Tang (2008), and Mendoza (2014).

A combination of rising world oil prices and peso depreciation turned the OPSF from a stabilization mechanism into a direct subsidy for fossil fuels (Mendoza, 2014). According to the Philippine Department of Energy (DOE), the government subsidized the fund with a total of 17.6 billion pesos (USD 1.1 billion in today's currency) between 1990 and 1997, which is equal to 0.8% of the total central government expenditures during the same time (Beltran, 2011).[4] The Philippine OPSF thus clearly fulfills the definition of a fossil fuel subsidy. Alternatively, these funds could have been used to build 62'000 schools or to provide free rice for 17 months to the poorest 30% of the population (Beltran, 2011). More relevant to the present thesis, the OPSF also had a negative impact on the climate. Transportation accounts for 40% of total energy consumption in the Philippines and uses mostly oil (Mendoza, 2014). The underpricing induced by the OPSF encouraged overconsumption of fossil fuels, increasing the burden on the environment. The DOE estimates that political pricing led to an overall increase of 26% in traffic and caused additional emissions of approximately 400'000 tons of CO_2 equivalent annually between 1991 and 1995 (Beltran, 2011).[5] This raises the question of what impact the abolishment of the OPSF had on carbon emissions from transport in the subsequent years? The present thesis aims to answer this question empirically by applying the synthetic control method.

[4] Author's own conversion to today's currency based on data from Beltran (2011) and Mendoza (2014), using consumer price indices from the World Bank (2022a).

[5] Assuming a conversion rate of nitrogen oxide to CO_2 of 298 (Eurostat, 2022).

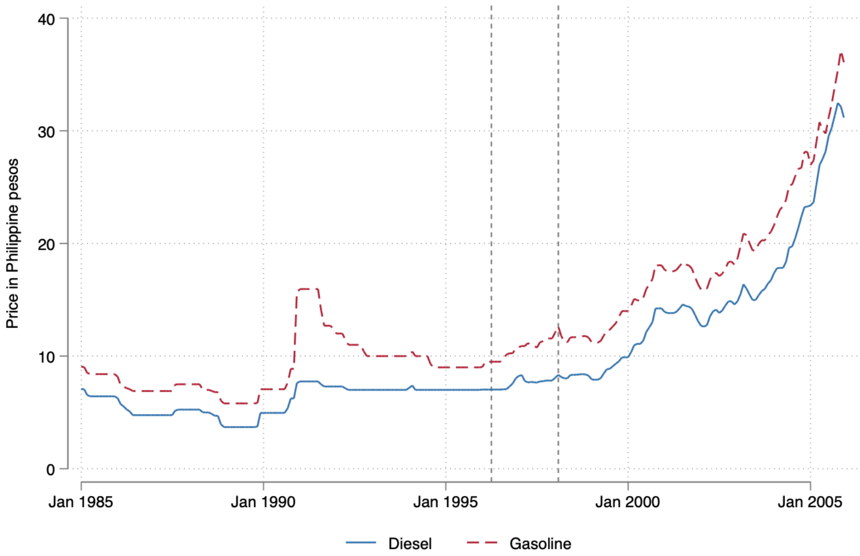
2.3 Impact on Fuel Prices

This section attempts to assess to which extent fuel prices rose as a result of the 1996 reform in order to be able to evaluate whether fuel consumption and hence also emissions from transport decreased as a result. Understanding this link is crucial for a clear attribution of the treatment effect to the 1996 fossil fuel subsidy reform under the synthetic control method.

I begin the analysis by looking at gasoline and Diesel prices in the Philippines before and after the reform, as depicted in Figure 1. The two vertical lines mark the first and the second reform attempt in March 1996 and February 1998 respectively. With the exception of a short spike in gasoline prices around 1991 in connection with the Iraqi invasion of Kuwait (Mendoza, 2014), fuel prices were very stable during the time the OPSF was in operation.[6] It can be seen how before the reform, prices were set by the government at regular intervals and did not fluctuate as much. This changed after the first reform attempt in 1996. During the transition phase following the reform, gasoline, and also to a lesser extent Diesel prices, started to trend upwards and move more instantaneously. This tendency becomes even stronger after the second and final reform attempt. Thereafter, prices were fully market-determined and strongly increased as a result of a combination of rising international oil prices, currency depreciation, and the abolishment of the OPSF. For a clear attribution of the effect, it is important to analyze to what extent this price increase was unique to the Philippines and driven by the 1996 subsidy reform.

[6] Diesel is mostly used for public transport in the Philippines and subsidized preferentially by the government (Mendoza, 2014). This might be the reason why Diesel prices did not appreciate to the same extent as gasoline prices during the invasion of Kuwait.

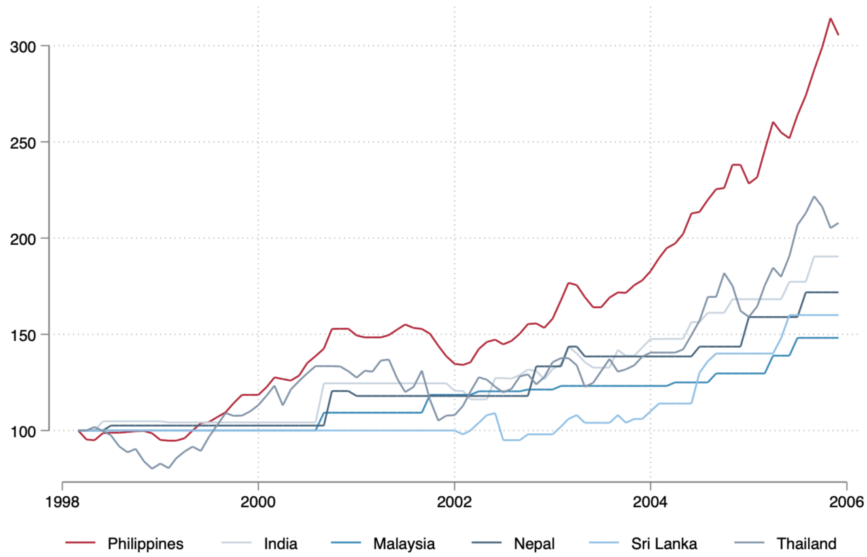
Figure 1: Monthly Gasoline and Diesel Prices in Local Currency



Note: The two vertical lines mark the first and the second reform attempt in March 1996 and February 1998 respectively. Price data was obtained from Kpodar and Abdallah (2017).

This can be analyzed by looking at Figure 2, which shows gasoline prices after 1998 in comparable countries, where data was available. Prices are in the local currency of each country and indexed at one hundred in March 1998. Unfortunately, not enough data is available to produce a similar graph for Diesel prices. From Figure 2, it can be seen that gasoline prices in the Philippines increased more pronounced than in comparable countries after the reform in 1998. For example, between 1999 and 2001, gasoline prices in the Philippines increased by 50% compared to 15-25% in the other countries. By the end of 2005, prices in the Philippines had more than tripled, while in most other countries they had less than doubled. The underlying hypothesis is that this stronger effect in the Philippines is due to catch-up effects of previously subsidized, low domestic prices rising to international levels after the abolition of the OPSF. Figure 2 deliberately does not account for inflation because it aims to capture price increases as perceived by customers. Moreover, oil prices are known to be a central driver of inflation. If inflation picks up as a result of higher fuel prices stemming from the subsidy reform, it is an integral result of the policy and should be included and not corrected for in the analysis. Nevertheless, even when adjusting for inflation, the Philippines still show a stronger increase in prices than most other countries (See Appendix A.4).

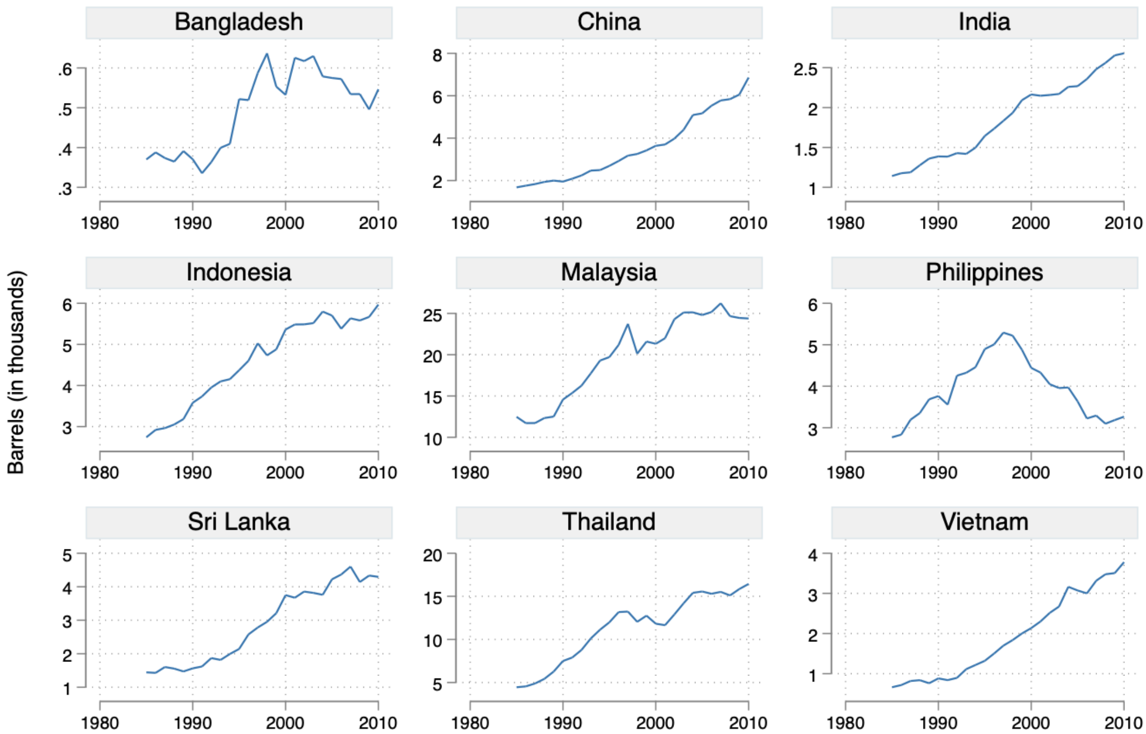
Figure 2: Gasoline Prices Indexed in Local Currency



Note: Gasoline prices are in local currency and indexed at one hundred at the beginning of March 1998. Monthly price data was obtained from. Kpodar and Abdallah (2017).

The next question is whether these higher prices resulted in a reduction in oil consumption. The Philippine DOE states that due to the 1996 reform, petroleum consumption growth dropped from 7.9% between 1984 and 1997 to 3.1% between 1997 and 2012 (Beltran, 2011). Likewise, Mendoza (2014) states that the increase in fuel prices motivated the use of less fuel-consuming vehicles, and overall energy efficiency improved as a result. She concludes that fuel subsidies clearly encouraged greater fuel consumption. These observations are supported by Figure 3, which shows oil consumption per capita for countries in the region, where data was available. As in other countries, oil consumption in the Philippines increased strongly after 1985. However, in contrast to other countries, Philippine oil consumption peaked in 1998, coinciding with the full liberalization of the downstream oil industry, and decreased sharply thereafter. Looking at Figure 3, it becomes evident that the Philippines are the only country showing such a peak in consumption.

Figure 3: Oil Consumption per One Million Inhabitants in Barrels per Day



Note: Author's own elaboration based on data from BP (2021). Singapore has been omitted from the panel due to its economic dissimilarity compared to the Philippines. Likewise, Pakistan has been excluded because it carried out a fossil fuel subsidy reform during the same time.

Given the descriptive analysis above, it seems plausible that the 1996 subsidy reform and the abolishment of the OPSF indeed led to higher fuel prices in the Philippines, which in turn led to lower fuel consumption and emissions from transport. The policy change of interest occurred at a discrete point in time, but the actual treatment to consumers builds over time and is dependent on other factors, such as developments in international oil prices and other shocks. Due to this complexity, it does not suffice to just look at fuel price elasticities to estimate the effect of the reform. The econometric challenge is to separate the effect of the 1996 fossil fuel subsidy reform on fuel prices and consumption from these other external shocks and the underlying macroeconomic trends. I solve this challenge by constructing a synthetic counterfactual from a pool of donor countries that mimics the Philippines in all aspects, but where the 1996 reform did not take place. By comparing GHG emissions from transport in the synthetic Philippines with the GHG emissions in the actual Philippines, I am able to filter out the emission reduction caused by the 1996 fossil fuel subsidy reform from all other factors.

3 Literature Review

This chapter provides an introduction to the relevant empirical literature concerning the environmental effects of carbon pricing and fossil fuel subsidies. While it is collectively agreed that carbon pricing is an indispensable policy tool to fight climate change, it is surprising how little causal empirical evidence there is on the actual performance of carbon pricing in reducing emissions (Green, 2021). Considering the high political controversy associated with increasing fuel prices (see e.g., yellow vest protests in 2018), it is by far not clear whether limited political capital should be invested in promoting carbon pricing when other measures to fight climate change might be more efficient and less costly. The following section discusses a recent stream of research investigating carbon taxation using the synthetic control method, which is thematically and methodologically close to the present study. Thereafter, the second section discusses the most recent empirical research on fossil fuel subsidies and carbon emissions.

3.1 Analyzing Carbon Taxation using Synthetic Controls

This section provides a brief introduction to a stream of literature analyzing the emission reduction associated with carbon taxation using the synthetic control method.[7] In a nutshell, the synthetic control method solves the problem of a missing suitable comparison group that plagues many comparative studies by constructing a hypothetical control unit, the synthetic control, from a pool of unaffected, comparable units (Abadie et al., 2010; Abadie & Gardeazabal, 2003). The methodological underpinnings of the synthetic control method are discussed in more detail in Section 4.1. Given the growing importance of synthetic controls in the policy evaluation literature, it comes as no surprise that they recently also found their application in the literature on carbon taxation. This strand of literature is related to the present thesis in the sense that a subsidy is nothing else than a negative tax. Instead of increasing the price of a good, subsidies decrease it. The present thesis makes use of this similarity by applying the most recent methodological advancements developed by the literature on carbon taxation to study the emission impact of fossil fuel subsidies.

Andersson (2019) was one of the first to apply synthetic controls to study the reduction in emissions stemming from carbon taxation. By constructing a synthetic Sweden as a comparison unit, he finds causal and statistically significant evidence that GHG emissions

[7] For more a more general discussion of the carbon pricing literature please refer directly to Green (2021), Haites (2018) or Global Subsidies Initiative (2019).

decreased on average by 6.3% annually as a result of the Swedish carbon tax introduced in the early 1990s. Mideksa (2021) finds similar results using the synthetic control method in Sweden's neighboring country Finland. His results suggest that carbon emissions from transport are 27% lower in 2003 compared to the synthetic counterfactual as a result of the carbon tax introduced in 1990. These effects are not unique to the Nordics. For example, Runst and Höhle (2022) find that the German Eco Tax lowered emissions from transport by 11-16% during the first six years the tax was in place. Likewise, Pretis (2022) finds that North America's first major carbon tax in the Canadian province of British Columbia lowered transport emissions between 3-15% during the treatment period compared to the synthetic counterfactual. Besides the transport sector, synthetic controls have also been applied to study emission reductions in the housing sector (Runst & Thonipara, 2020) and the power industry (Leroutier, 2022).

The synthetic control method offers some major advantages for the study of carbon taxes. First and foremost, it solves the problem of a missing suitable comparison group and relaxes the parallel trends assumption, which inhibits many studies from using the Differences-in-Differences (DID) method, by allowing the effects of unobserved confounders to vary over time (Andersson, 2019; Pretis, 2022; Runst & Thonipara, 2020). Secondly, the contribution of each donor unit and the weights assigned to each predictor variable are made explicit under the synthetic control method (Abadie, 2021). This makes the results more transparent and easier to interpret. In addition, the selection of a suitable control group is carried out through a data-driven process and not left to the choice of the researcher (Abadie, 2021). Lastly, the synthetic control method allows to analyze emissions directly as the main outcome variable. This is an advantage over studies that rely on demand price elasticities for gasoline or Diesel to estimate the environmental effects of carbon taxes (Andersson, 2019). By focusing on elasticities only, these studies fail to incorporate fuel switching, for example from gasoline to Diesel, and substitution between different modes of transport (Andersson, 2019). Synthetic controls, on the other hand, allow to capture emission reduction effects on both the intensive (reduction in consumption) and the extensive margin (fuel and transport switching).

As becomes evident from the discussion above, synthetic controls offer many advantages, which explains their rapidly increasing popularity in the literature on carbon taxation. Given the economic similarity of taxes and subsidies, the same advantages should apply to the study of subsidies. To the best of my knowledge, the present thesis constitutes the first attempt to study the emission effects of fossil fuel subsidies using the synthetic control method. In this sense, the present thesis builds on the recent experiences using synthetic controls in the literature on carbon taxation and expands the use of the methodology to a new field of research.

3.2 Fossil Fuel Subsidies and GHG Emissions

This section discusses the relevant literature on fossil fuel subsidies and climate change. Most of the research on fossil fuel subsidies up to the current date has focused on the associated social and distributional effects. There is a broad consensus in the literature that fossil fuel subsidies crowd out public social spending and are an inefficient policy to support lower-income groups, as they often tend to be regressive and benefit wealthier households more than poorer ones (Couharde & Mouhoud, 2020). While the social and distributional effects of fossil fuel subsidies are well researched, little attention has been paid to the associated environmental externalities (Ellis, 2010; Mundaca, 2017; Rentschler & Bazilian, 2017). This is especially true with respect to empirical ex-post studies (Ellis, 2010; Global Subsidies Initiative, 2019; Solarin, 2020). Whilst there is broad consensus in the literature that phasing out fossil fuel subsidies would significantly reduce GHG emissions (Sovacool, 2017), there is little to no empirical evidence proving that this is indeed the case. Moreover, most studies investigating the environmental effect of fossil fuel subsidies and fuel consumption have focused on developed countries and much more research is needed on developing economies (Mundaca, 2017). The latter is of particular importance considering that most fossil fuel subsidies today are concentrated in Asian and Middle Eastern countries (Parry et al., 2021).

Already more than three decades ago, Kosmo (1987) noted that phasing out subsidies on the most polluting fossil fuels would significantly contribute to solving the world's environmental problems. Larsen and Shah (1992) were the first ones to estimate the global emission reduction potential associated with eliminating fossil fuel subsidies. According to their model, removing fossil fuel subsidies would reduce GHG emissions globally by 5-9%. While later studies estimated similar GHG reduction potentials of around 6-10% (Burniaux & Chateau, 2014; Schwanitz et al., 2014), more recent studies are more conservative and expect that the global reduction potential is more around 1-4% (Chepeliev & van der Mensbrugghe, 2020; Jewell et al., 2018). Still, there is broad consensus in the literature that phasing out fossil fuel subsidies would lead to lower GHG emissions (Sovacool, 2017). However, it is important to note that all of these estimates are predictions based on models and not empirical observations.

The empirical literature focusing on the GHG abatement potential associated with phasing out fossil fuel subsidies is still nascent and sparse. While Rentschler and Bazilian (2017) note that there is a thorough literature on general reform experiences with consumer subsidies, only very little is known about the actual emission reduction stemming from phasing out fossil fuel subsidies. As with carbon taxation, it is of great interest to better understand the effectiveness of phasing out fossil fuel subsidies in reducing GHG emissions, especially considering the high political cost involved with raising fuel prices. In a recent study, Solarin (2020) examines a panel dataset of 35 emerging and developing countries and finds that a 10% increase in fossil fuel subsidies increases the ecological footprint by 0.3-1.5%. The ecological footprint serves as a proxy for overall environmental degradation and includes factors such as carbon emissions and land use. In a similar study covering 18 developing countries, Solarin and Al-Mulali (2021) find that a 1% increase in per capita fuel subsidies is associated with an increase of 0.041-0.094% in CO_2 emissions from transport. While this effect is relatively small in magnitude, they note that eliminating fossil fuel subsidies is a crucial step towards reducing GHG emissions from transport and call for more research in the area.

From the short discussion above it becomes evident that although there is broad consensus in the literature about the positive environmental effect of eliminating fossil fuel subsidies, there is very little empirical evidence documenting this. This is not too surprising considering that empirical ex-post research on the more salient topic of carbon pricing picked up only recently. Consequently, both Sovacool (2017) as well as Rentschler and Bazilian (2017), and indirectly also Green (2021), call for more research on the impact of fossil fuel subsidy reforms on emission reductions to evaluate their role in a comprehensive climate change policy. The present thesis aims to answer this call by studying the GHG emission reduction associated with phasing out transport fossil fuel subsidies at the example of the 1996 subsidy reform in the Philippines. To the best of my knowledge, the present paper is one of the first attempts to present ex-post empirical evidence on the reduction in GHG emissions associated with phasing out fossil fuel subsidies. The focus thereby lies on emissions from the transport sector given the direct impact of eliminating oil subsidies on fuel prices.

4 Methodology

This chapter describes the methodology used in the present paper. The first section provides a brief overview of the conceptual framework and the mathematical structure of the synthetic control method. The second section discusses the specification of the main model with respect to the composition of the donor pool, the selection of predictor variables, and the choice of the observation period.

4.1 The Synthetic Control Method

The following section offers a brief introduction to the synthetic control method. First, the conceptual framework is provided to facilitate the overall understanding of the method. Then, the underlying technical theory is explained in more detail.

4.1.1 Conceptual Framework

The synthetic control method was first introduced by Abadie and Gardeazabal (2003) to study the economic effects of the terrorist conflict in the Basque Country in the late 1960s. Since then, the method has undergone substantial further development and was enhanced with additional inference techniques (Abadie, 2021; Abadie et al., 2010, 2015). More recently, Doudchenko and Imbens (2016) and Athey et al. (2021) extended the basic version of the synthetic control method by relaxing certain restrictions on weights and applying matrix completion methods. Athey and Imbens (2017, p. 9) describe the synthetic control method as "arguably the most important innovation in the policy evaluation literature in the last 15 years".

Synthetic control methods solve the problem of a missing control counterfactual many comparative studies suffer from by constructing a hypothetical comparison unit – the synthetic control – as a weighted average of comparable units, often referred to as the donor pool.[8] The underlying assumption is that patterns across units are stable over time, which allows the construction of an unaffected control unit from the donor pool even after treatment took place. More formally, assume each row in matrix M corresponds to a single unit and each column refers to a specific point in time. In this matrix M, every observable and known outcome is denoted with a ✓ symbol and every unobserved outcome is marked with a question mark. As can be seen below, all outcomes but the counterfactual outcomes

[8] The following paragraph is based in big parts on Athey et al. (2021).

of the unit of interest after receiving treatment are known. The challenge at hand is to estimate the counterfactual outcomes of the treated unit for a hypothetical case where treatment did not occur. The synthetic control method does this by (vertically) regressing the outcomes of the treated unit prior to receiving treatment on the outcomes of all other units in each period and then predicts the hypothetical outcomes where the unit of interest did not receive treatment based on the previously obtained coefficients for the time after treatment took place (Doudchenko & Imbens, 2016; Ferman & Pinto, 2021). In the basic case, the coefficients must not be negative and have to sum to one. In other words, the synthetic control method takes all the known data points (the checkmarks ✓) and tries to construct missing data points for the treated unit (the question marks ?) as a weighted average of the other units in the same period. The estimated question marks together then form a synthetically constructed control unit where treatment did not take place. The big advantage of the synthetic control method is that it offers a transparent, data-driven approach to solving the problem of a missing counterfactual (Abadie, 2021).

$$M = \begin{bmatrix} \checkmark & \checkmark & \checkmark & \checkmark & \dots & \checkmark \\ \checkmark & \checkmark & \checkmark & \checkmark & \dots & \checkmark \\ \checkmark & \checkmark & \checkmark & \checkmark & \dots & \checkmark \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \checkmark & \checkmark & \checkmark & \checkmark & \dots & \checkmark \\ \checkmark & \checkmark & \checkmark & ? & \dots & ? \end{bmatrix}$$

Synthetic control methods are best suited to analyze the impact of an intervention or policy that affects the unit of interest as a whole on the aggregate level (Abadie, 2021). For example, Abadie et al. (2015) applied the synthetic control method to study the economic impact of the German reunification on West Germany. Other applications include studies on the effects of natural disasters (Cavallo et al., 2013), tobacco control policies (Abadie et al., 2010) or on the economic effects of the Brexit referendum (Born et al., 2019). More recently, synthetic control methods have found their application also increasingly in the area of environmental economics. Andersson (2019) studied the effect of emission taxation in the Swedish transport sector and was the first one to find a significant causal effect. Since then, several papers studied the impact of carbon taxation on GHG emissions using synthetic control methods (e.g., Leroutier, 2022; Pretis, 2022; Runst & Höhle, 2022; Runst & Thonipara, 2020).

4.1.2 Theory

The following section explains the mathematical foundations of the synthetic control method based on the presentation in Abadie (2021) and Abadie et al. (2015). Suppose a sample with data on $J + 1$ units with unit $j = 1$ being the unit of interest receiving treatment and the remaining units $j = 2, 3, \ldots, J+1$ forming a "donor pool" of untreated comparison units. All units are observed for a time interval of $T(t = 1, 2, \ldots, T)$ periods with T_0 pretreatment periods $(t = 1, 2, \ldots, T_0)$ and T_1 post-treatment periods $(t = T_0 + 1, T_0 + 2, \ldots, T)$. The first period the treated unit, $j = 1$, is exposed to treatment is thus $T_0 + 1$. The outcome of interest is denoted as Y_{jt}, where j refers to the unit and t to the time of observation. The potential outcome of unit j in periods without intervention taking place can now be defined as Y_{jt}^N. Similarly, for the treated unit, $j = 1$, the treated outcomes during the post-treatment periods T_1 can be defined as Y_{1t}^I. The two variables defined above correspond to the potential outcome variables in Rubin's causal inference model (Rubin, 1974). The treatment effect for the affected unit, $j = 1$, in period $t > T_0$ is then:

$$\tau_{1t} = Y_{1t}^I - Y_{1t}^N. \tag{4.1.1}$$

Now because the unit of interest, $j = 1$, is affected by the treatment during the post-treatment periods T_1, we only observe treated outcomes and $Y_{1t} = Y_{1t}^I$ for periods $t > T_0$. The econometric challenge is now to predict the counterfactual outcome Y_{1t}^N for the post-treatment periods T_1 as if treatment would not have taken place. The synthetic control method attempts to estimate Y_{1t}^N as a weighted combination of units in the donor pool. The underlying idea is that a weighted combination of units with similar characteristics approximates the counterfactual outcome of the treated unit better than any single comparison unit alone.

The synthetic control can be represented as a $J \times 1$ vector of weights, $\mathbf{W} = (w_2, w_3, \ldots, w_{j+1})$, where w_j represents the individual weight assigned to unit j in the donor pool. The synthetic control estimators of $\hat{Y}_{1t}^N$ and τ_{1t} are then

$$\hat{Y}_{1t}^N = \sum_{j=2}^{J+1} w_j Y_{jt} \tag{4.1.2}$$

and

$$\hat{\tau}_{1t} = Y_{1t} - \hat{Y}_{1t}^N. \tag{4.1.3}$$

In the canonical case, weights are restricted to be nonnegative and sum to one to avoid extrapolation. However, these restrictions have been challenged recently.[9] Because the distribution of the individual weights $w_2, w_3, \ldots, w_j$ largely determines the final shape of the synthetic control, how they are assigned is a crucial question.

Abadie and Gardeazabal (2003) and Abadie et al. (2015) suggest choosing the weights in a manner that the constructed synthetic control approximates the pre-intervention values of the treated unit based on a set of variables predicting the outcome variable. Formally, for each unit j, a set of k predictors is observed and denoted as $X_{1j}, X_{2j}, \ldots, X_{kj}$. The predictor variables should be correlated with the outcome variable and may also include pre-treatment values of the outcome variable itself. The predictors of each unit can then be written as $k \times 1$ vectors $\mathbf{X}_1, \mathbf{X}_2, \ldots, \mathbf{X}_{j+1}$ and stacked together to form a $k \times J$ matrix, $\mathbf{X}_0 = [\mathbf{X}_2, \mathbf{X}_3, \ldots, \mathbf{X}_{J+1}]$ containing the predictor variables of all J untreated units. Given a set of nonnegative constants $\mathbf{V} = (v_1, v_2, \ldots, v_k)$, Abadie and Gardeazabal (2003) and Abadie et al. (2015) propose to choose the vector of weights, $\mathbf{W}^*$, that minimizes

$$\|\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}\| = \left(\sum_{h=1}^{k} v_h (X_{h1} - w_2 X_{h2} - \ldots - w_{J+1} X_{hJ+1})^2\right)^{1/2} \tag{4.1.4}$$

subject to the constraints that the weights $w_2, w_3, \ldots, w_{J+1}$ are nonnegative and sum to one. As mentioned before, these two constraints can be relaxed in more advanced applications of the synthetic control method. The constants $v_1, v_2, \ldots, v_k$ in Equation (4.1.4) indicate the relative importance of each of the k predictor variables in reproducing the treated unit $X_{11}, \ldots, X_{k1}$. For each set of constants $\mathbf{V}$, minimizing Equation (4.1.4) produces a synthetic control, $\mathbf{W}(\mathbf{V}) = (w_2(\mathbf{V}), w_3(\mathbf{V}), \ldots, w_{J+1}(\mathbf{V}))$. The question now is how to choose the set of constants $\mathbf{V}$. Abadie and Gardeazabal (2003) and Abadie et al. (2015) propose to choose $\mathbf{V}$ so that it reduces the Mean Square Prediction Error (MSPE) of the resulting synthetic control $\mathbf{W}(\mathbf{V})$ with respect to Y_{1t}^N. Formally, they suggest choosing the $\mathbf{V}$ that minimizes

$$\sum_{t \in \mathcal{T}_0} (Y_{1t} - w_2(\mathbf{V}) Y_{2t} - \ldots - w_{J+1}(\mathbf{V}) Y_{J+1t})^2 , \tag{4.1.5}$$

for the pre-intervention periods $\mathcal{T}_0 \subseteq \{1, 2, \ldots, T_0\}$. Once the vector of constants $\mathbf{V}^*$ is found, the optimal vector of weights $\mathbf{W}^*$ can be obtained from Equation (4.1.4). This nested minimization approach has proven to yield the most precise results (McClelland

[9] See for example Doudchenko and Imbens (2016) or Ferman and Pinto (2021).

& Gault, 2017). Lastly, the synthetic control counterfactual and the treatment effect can be estimated by plugging in the values of $\mathbf{W}^*(\mathbf{V}^*)$ into Equation (4.1.2) and combining it with Equation (4.1.3).

4.2 Model Specification

This section discusses the specification of the synthetic control method. The first subsection presents the donor pool and provides the reasoning for the exclusion of certain countries. The subsequent subsection discusses the selection of the predictor variables and the last subsection elaborates on the choice of time limits for the pre- and posttreatment period.

4.2.1 Donor Pool

This subsection presents the composition of the donor pool and discusses the reasons for the exclusion of certain countries. In order for the synthetic control method to provide a good comparison unit, the countries in the donor pool should be similar to the Philippines in their main characteristics (McClelland & Gault, 2017). This is important because if donor countries are very dissimilar from the treated unit, the synthetic control can introduce interpolation biases by just averaging away large discrepancies between the donor countries and the treated unit (Abadie, 2021). The countries from the Association of Southeast Asian Nations (ASEAN) provide a good starting point because of their geographic proximity and economic similarity to the Philippines. The ASEAN has ten members: Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam, which might be a little too few countries to form a good donor pool. This is especially true if certain countries have to be excluded from the donor pool at a later stage. For this reason, I extend the donor pool by adding the eight countries from the South Asian Association for Regional Cooperation (SAARC): Afghanistan, Bangladesh, Bhutan, India, the Maldives, Nepal, Pakistan, and Sri Lanka. Lastly, I add Papua New Guinea, which is not a member of either organization but is geographically close to the Philippines. This leaves us with an initial donor pool of 18 countries to start with.

Unfortunately, the availability of data on the predictor variables is rather limited for many countries. For this reason, Afghanistan, Laos, Cambodia, Papua New Guinea, Bhutan, the Maldives, and Singapore have to be dropped from the donor pool. Even if data were available, one might want to exclude Singapore, Afghanistan, and the Maldives because of their economic dissimilarity to the Philippines to avoid interpolation bias. For this reason, even though data is available for Brunei, I decide to exclude the oil-rich sultanate due to its stark economic dissimilarity to the Philippines. According to the World Bank (2022c), the GDP per capita in Brunei was 14 times higher in 1995 than in the Philippines. The inclusion of Brunei would thus pose a risk for interpolation bias.

Besides very dissimilar countries, one should also exclude countries that underwent a similar intervention than the country of interest from the donor pool (Abadie, 2021). The inclusion in the donor pool of countries that were treated themselves could lead to an underestimation of the treatment effect on the treated unit. In the case of the Philippines, treatment is equal to phasing out or reforming fossil fuel subsidies on gasoline and Diesel products. Several countries from the remaining donor pool made reform attempts between 1985 and 2005. For example, Pakistan carried out such a reform in 2000 and is thus excluded from the donor pool.[10] Similar to the Philippines, oil consumption decreased after the fossil fuel subsidy reform in Pakistan. The reform in Pakistan thus supports the narrative that fossil fuel subsidy reforms reduce oil consumption and potentially also GHG emissions. The reason why this paper focuses on the Philippines and not on Pakistan is that the reform in the Philippines was more transparent and more data is available. Besides Pakistan, Indonesia attempted to phase out its fossil fuel subsidies and tried to raise fuel prices several times between 1998 and 2005. However, most price increases had to be reversed shortly after implementation due to strong public and political opposition (Bacon & Kojima, 2006). The price increases that were not reversed were accompanied by rising oil prices and thus just kept the relative level of subsidies more or less stable (Beaton & Lontoh, 2010). A study by the IMF deemed all reforms in Indonesia before 2005 as failed and the latest reform in 2005 only as "partially successful" (Clements et al., 2013).[11] Even after the reform in 2005, Indonesia continued spending several billion USD and up to 3.5% of its GDP each year on oil subsidies (Beaton et al., 2013). Based on this and because the partially successful reform in 2005 occurred one year after the last posttreatment period, I decide to keep Indonesia in the donor pool. Another country that attempted to reform its fossil fuel subsidies is Thailand, which deregulated price setting for petroleum products in 1991 (Beaton et al., 2015). Yet, according to the International Institute for Sustainable Development (IISD, 2013), the government continued intervening in the setting of fuel prices even after the reform through its oil price stabilization fund. Moreover, when international oil prices began to rise in 2003, the Thai government officially reintroduced price ceilings and subsidies for both gasoline and Diesel (Bacon & Kojima, 2006; IISD, 2013). Because the subsidies were not phased out completely and reintroduced eventually, I decide to include Thailand in the donor

[10] See Malik (2007) for more information on the reform in Pakistan.

[11] The same study by Clements et al. (2013) assesses the 1996 reform in the Philippines as successful.

pool. After all, if the decision to keep Thailand introduces a bias, it would most likely reduce the treatment effect as a part of the synthetic control underwent treatment as well. Hence, in the worst case, the inclusion of Thailand leads to more conservative results. In any case, robustness checks carried out in Section 6.2 show that the direction and size of the overall results do not change a lot with respect to the inclusion of Thailand. To the best of my knowledge, there were no other noteworthy reforms carried out by donor pool countries besides the ones mentioned above.

Finally, in addition to countries that are structurally different and underwent treatment themselves, one should also exclude countries that have suffered large idiosyncratic shocks from the donor pool to obtain unbiased results (Abadie, 2021). With respect to this, Sri Lanka requires some further discussion because of the civil war from 1983 until 2009. On the one hand, one could argue that this civil war represents such an idiosyncratic shock and that Sri Lanka should be excluded from the donor pool. However, because the war spans the whole time period analyzed in the present paper, it can be interpreted like a fixed effect pertaining to Sri Lanka. In other words, any effects of the war are factored in during the matching phase of the synthetic control and are present also after treatment occurred. The underlying assumption is that there are no substantial changes in the effect of the war on the outcome and predictor variables during the analysis period. I consider the above reasonable and therefore include Sri Lanka in the donor pool. The final donor pool is thus reduced from eighteen to nine countries and is summarized in Table 2. The relatively small size of the donor pool is thereby mostly due to the limited data availability for a number of countries in the region.

Table 2: Donor Pool Countries

Country	Group	Donor Pool	Exclusion Reason	Comments
Brunei	ASEAN	No	Dissimilar economically	Dissimilar economically
Cambodia	ASEAN	No	Data availability	
Indonesia	ASEAN	Yes	-	Several failed reform attempts between 1998 and 2005
Laos	ASEAN	No	Data availability	
Malaysia	ASEAN	Yes	-	
Myanmar	ASEAN	Yes	-	
Singapore	ASEAN	No	Data availability	Dissimilar economically
Thailand	ASEAN	Yes	-	Reform in 1991, but subsidies were reintroduced in 2003
Afghanistan	ASEAN	No	Data availability	Afghanistan war from 2001 on
Vietnam	ASEAN	Yes	-	
Bangladesh	SAARC	Yes	-	
Bhutan	SAARC	No	Data availability	
India	SAARC	Yes	-	Attempted reform in 2002, price controls remained
Maldives	SAARC	No	Data availability	Dissimilar economically
Nepal	SAARC	Yes	-	
Pakistan	SAARC	No	Reform in 2000	
Sri Lanka	SAARC	Yes	-	Civil War 1983 - 2009
Papua New Guinea	-	No	Data availability	

Note: Author's own elaboration.

4.2.2 Variable Selection

The following subsection discusses the selection of the predictor variables in more detail. As with any predictive model, the selection of the predicting variables is of great importance in synthetic control models (Abadie, 2021). Ideally, predictors should affect the outcome variable both before and after treatment in a relatively stable manner (McClelland & Gault, 2017). An important predictor is thereby the lagged value of the outcome variable itself. Including lagged observations of the main outcome can substantially improve the pretreatment fit of the synthetic control. Furthermore, including lags of the outcome variable mitigates the problem of omitted variables as the lags include the effect of any potential predictor variable, independent of whether it is observable and included in the model or not (McClelland & Gault, 2017). However, as Kaul et al. (2021) point out, one should never include all pretreatment lags because this renders all other predictor variables meaningless. They suggest including the last lag of the outcome variable or the average over the pretreatment period. Yet, Ferman et al. (2020) note that there exists no consensus on how to select the right amount of lags in synthetic control models, which can lead to cherry-picking and specification searches. They suggest presenting the results of several specifications to give the reader an idea of the sensitivity of the model with respect to the number of lags. While McClelland and Gault (2017) generally recommend choosing a small number of lags, Abadie (2021) comments that the researcher has some flexibility with respect to the choice of the lagged outcomes as long as a sufficiently good pretreatment fit is attained.

The variable selection for the present analysis is inspired in big parts by the setup in the Andersson (2019) paper on carbon taxes and CO_2 emissions from the Swedish transport sector. However, due to the limited data availability for many countries in the donor pool, some predictors had to be dropped and replaced with others. As in Andersson (2019), I use GDP per capita, share of urban population and gasoline consumption per 1000 inhabitants as predictor variables. In addition, I include Diesel consumption per 1000 inhabitants and energy use per capita. GDP per capita is known to be closely linked to GHG emissions from existing literature (Dinda, 2004) and the degree of urbanization is negatively related to CO_2 emissions (Neumayer, 2004). Growth in energy use per capita is closely related to growth of motorized transport and related GHG emissions, especially in developing countries (World Bank, 2022b). In contrast to Andersson (2019), I do not use the number of motor vehicles as a predictor because the data is not available for most Asian countries in the 1980s and 1990s.

With respect to the selection of lagged outcomes, I slightly depart from the specification chosen by Andersson (2019). Instead of three lags, I choose to add only two lags corresponding to the beginning and the end of the pretreatment phase in 1985 and 1995 respectively. The reason for this is that the pretreatment fit of a model with two lags (RMSPE: 0.0057) is only negligibly worse than that of a model with a third outcome lag in 1990 (RMSPE: 0.0053).[12] However, the country weights in the specification with two lags are more sparse and easier to interpret compared to the specification with three lags, where several countries receive weights smaller than one percent. The specification using the average of the outcome variable during the pretreatment period suggested by Kaul et al. (2021) has an equally good pretreatment fit (RMSPE: 0.0057) but puts a weight of 90% on the lagged emission variable. While such high predictor weights are not unusual for synthetic controls, it is exactly the case Kaul et al. (2021) aim to avoid. Lastly, applying the other specification recommended by Kaul et al. (2021), using only the last outcome lag, leads to a substantially worse pretreatment fit (RMSPE: 0.0499). Based on the above, the specification with two lags in 1985 and 1995 respectively seems to be the most appropriate. For completion, as recommended by Ferman et al. (2020) the main results with the other three specifications can be found in Appendix A.5. The differences in outcome between the three specifications with a low RMSPE are negligible. The main results are thus not sensitive to the selection of outcome lags.

4.2.3 Time Period

This subsection discusses the delimitation of the pretreatment and posttreatment periods as well as the timing of treatment. The pretreatment period starts in 1985, the first year entirely covered by the OPSF. Prior to the inception of the OPSF in October 1984, petroleum product prices were determined by the market without major government intervention (Mendoza, 2014). Because the synthetic control should replicate the path of emissions under the OPSF, it cannot be fitted prior to 1985. Treatment occurred in 1996 with the first attempt to reform fossil fuel subsidies. Even though the first reform attempt was declared unconstitutional and prices were only fully liberalized in 1998 (U et al., 2021), I choose 1996 as the treatment period to capture any potential anticipation effects. This is in line with the interpretation of U (2000, p. 3) who writes: "With the passage of the original Downstream Oil Industry Deregulation Act, RA 8180, in 1996, the industry finally completed the cycle from free to regulated and back to free market". Lastly, I choose 2004 as the final posttreatment period because of several reasons. First of all, in 2005 the Philippine government removed the VAT exemption on petroleum products, which led to an increase in fuel prices (Mendoza, 2014). Moreover, in August 2005 the Philippine government began to require oil companies to justify any increase in fuel prices and sometimes even demanded prices to be slightly lowered to mitigate the effects

[12] The RMSPE is equal to the root of the MSPE.

of the rapidly rising international oil prices (Bacon & Kojima, 2006). Lastly, during the same year, the government launched a new energy plan with the aim of promoting energy efficiency and conservation. As part of this plan, a four-day working week was introduced for two months and government offices were mandated to reduce their fuel consumption by 10% (Bacon & Kojima, 2006). Because the emission effects of the three aforementioned policy changes cannot be disentangled from the effect of the subsidy reform in 1996, I choose 2004 as the final period of observation. This leaves us with a pretreatment period from 1985-1995 and a posttreatment period from 1996-2004.

5 Data

In this chapter, the data used in the study at hand is presented and described. The first section discusses the data on GHG emissions used for the main outcome variable in more detail and the second section presents the data used for the covariates.

5.1 Emission Data

The data on GHG emissions from the transport sector was obtained from the Emissions Database for Global Atmospheric Research (EDGAR) by the European Union (Crippa et al., 2021). The EDGAR database contains sector-specific, yearly time-series data on GHG emissions for 207 countries from 1970 until 2018. Greenhouse gases include carbon dioxide (CO_2), methane (CO_4), nitrous oxide (N_2O), and fluorinated gases (Crippa et al., 2021). The EDGAR database accounts for differences in technology and factors in emissions reductions from the installment of abatement systems as well. Due to its good comparability across countries, the EDGAR database has enjoyed increasing popularity in research and has been used for example by Mideksa (2021) or Pretis (2022).

The emission data is categorized according to the official sectorial classification developed by the Intergovernmental Panel on Climate Change (IPCC). For the present paper, I use annual data from 1985 to 2004 on GHG emission from the transport sector measured in metric tons of CO_2 equivalent. The transport sector includes emissions from road and non-road transport, as well as domestic aviation and inland waterways. I combine the emission data with population data from the World Bank (2022d) to obtain transport GHG emissions per capita. Dividing total emissions by population adjusts for the difference in the size of countries and makes the data more comparable across states. The main outcome variable of the present analysis is thus defined as annual transport GHG emissions per capita in tons of CO_2 equivalent.

5.2 Covariates and Country Characteristics

In addition to the main outcome variable, a set of covariates are crucial to ensure a good fit when using the synthetic control method. Covariate variables should be related to the main outcome variable in order to be able to predict it in the posttreatment period (McClelland & Gault, 2017). For this reason, covariates are also often referred to as predictor variables in the synthetic control literature. In the following, I provide the data sources of the five predictor variables. The reasoning behind the selection of the predictor variables is discussed in more detail in Subsection 4.2.2.

The five predictor variables are GDP per capita, share of urban population, energy use per capita and Diesel and gasoline consumption per 1000 inhabitants. Data on energy use per capita was obtained from the World Bank (2022b). Energy use refers to the use of primary energy before transformation to other end-use fuels and is measured in kg of oil equivalent per capita. Likewise, data on the share of urban population was collected from the World Bank (2022e). Expenditure-side real GDP was obtained from the Penn World Tables (Feenstra et al., 2021) because of better data availability than at the World Bank. As in Andersson (2019), real GDP is at chained purchasing power parity (PPP) and is divided by population, for convenience also obtained from the Penn World Tables. Data on gasoline and diesel consumption was retrieved from the World Development Indicator database archive (World Bank, 2022f) and adjusted with population data from the World Bank (2022d).

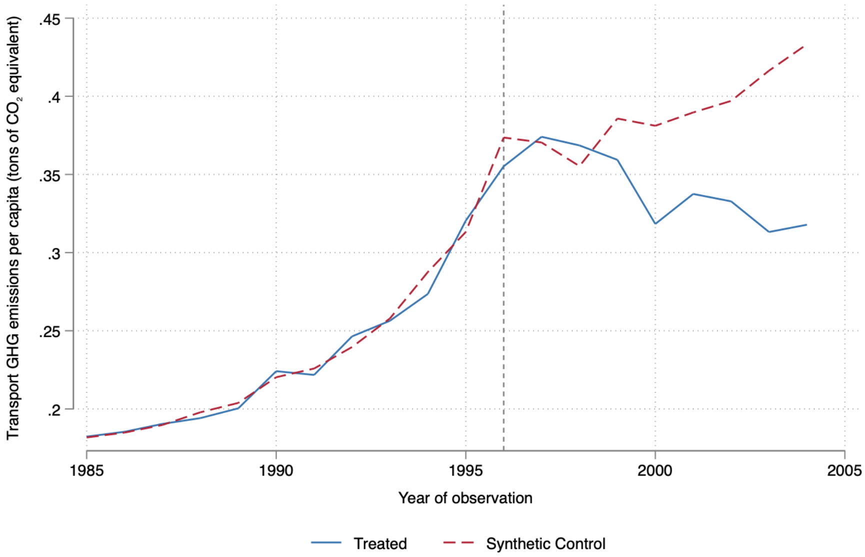
6 Empirical Analysis

This chapter presents the results from the empirical analysis and discusses their robustness. First, the main results are presented and the composition of the synthetic control is scrutinized. Thereafter, the robustness of the results and the underlying model is tested using several robustness checks. Lastly, the statistical significance of the results is briefly discussed.

6.1 Analysis and Results

The main results of the synthetic control analysis are shown in a path plot in Figure 4. The graph shows the GHG emissions from transport for the synthetic Philippines versus the real Philippines. The better the synthetic control replicates the actual Philippines during the pretreatment period, the higher is the credibility of the identification assumption that the synthetic control represents the path of emissions from 1996 until 2004 in the absence of treatment. From the graph, it appears that the synthetic Philippines track the trajectory of GHG emissions of the actual Philippines relatively well during the pretreatment phase and diverge only after treatment happened in 1996. The divergence of the two lines only after treatment occurred but not before is an indication that the fossil fuel subsidy reform indeed had an effect on GHG emissions. The average absolute tracking error between synthetic and real Philippines during the pretreatment period is only 0.004 tons of CO_2. The RMSPE during the pretreatment period is equal to 0.0057. Just after treatment occurred, there is a slight dent in the synthetic control emissions. This dent is probably caused by the 1997 Asian financial crisis and is most likely unrelated to the subsidy reform in the Philippines. Overall, the relatively good fit during the pretreatment period adds to the credibility of the synthetic control.

Figure 4: Path Plot of Synthetic Philippines vs. Actual Philippines



The composition of the synthetic control is shown in Table 3. The synthetic Philippines are made up of five countries: Indonesia (14%), Malaysia (7%), Myanmar (12%), Sri Lanka (57%), and Thailand (10%). The other countries in the donor pool are assigned a weight of zero. With 57%, Sri Lanka receives the biggest weight and makes up more than half of the synthetic control. This might come as a bit of a surprise as Sri Lanka does not lie in immediate geographic proximity of the Philippines. However, Sri Lanka's big weight might be explained by the fact that its average GDP per capita during the pretreatment phase from 1985-1995 is comparatively close to the average GDP per capita of the Philippines. Of all the donor countries, only Indonesia has an average pretreatment GDP per capita closer to the Philippines. Given that GDP per capita is closely related to GHG emissions, the big weight on Sri Lanka can be rationalized. Nevertheless, such a big weight on a single country raises the question whether the results are driven by Sri Lanka alone. This question is addressed in more detail in Section 6.2. The remaining four countries making up the synthetic Philippines all receive weights of around 10% each. Bangladesh, India, Nepal, and Vietnam are assigned zero weight and thus do not form part of the synthetic Philippines in this specification. Because the synthetic control method does not allow for extrapolation, the country weights are all non-negative and sum up to one.

The mean values of the predictor variables for the actual and the synthetic Philippines are shown in Table 4. For completion, also the average predictor values for the whole donor pool are displayed. The synthetic control approximates the actual Philippines relatively well in most variables. With the exception of urban population and gasoline consumption,

Table 3: Country Weights (W-Matrix)

Country	Weights	Country	Weights
Bangladesh	0	Nepal	0
India	0	Sri Lanka	.57
Indonesia	.14	Thailand	.10
Malaysia	.07	Vietnam	0
Myanmar	.12		

the values of the synthetic control differ less than 3% from the actual Philippines. The poor match in the other two variables can be explained by the weights the synthetic control algorithm attached to them. As can be seen in Table 5, gasoline consumption is weighted only with 5% and urban population receives a weight close to zero. Comparing the share of urban population with the average in the donor pool, it appears that the Philippines have a for the region unusually high degree of urbanization. Because the synthetic control method does not allow for extrapolation, it struggles to replicate such extreme values. This could be a reason for the close to zero weight on urban population and the resulting difference between the Philippines and its synthetic counterpart.

Table 4: Mean Values of Predictor Variables

Predictors	Philippines	Synth. Philippines	Donor Pool
GDP per capita	3707	3713	3114
Urban population (%)	45.6	24.4	25.4
Energy use per capita	452.8	456.0	467.6
Gasoline cons. (per 1000 people)	22.5	25.4	28.7
Diesel cons. (per 1000 people)	38.5	39.6	32.4
GHG per capita 1985	0.182	0.182	0.150
GHG per capita 1995	0.320	0.313	0.285

Note: All variables except lagged GHG emissions are averaged over the pretreatment period 1985-1995. GDP per capita is PPP adjusted and in 2017 US dollars. Energy use is measured in kilograms of oil equivalent per capita. Diesel and gasoline consumption is measured in tons of oil equivalent per 1000 inhabitants. GHG emissions are in tons of CO_2 equivalent per capita.

The predictor weights in Table 5 also show that the synthetic control assigns the biggest weights to the two lagged GHG emission variables. GHG emissions per capita in 1985 and 1995 receive a weight of 43% and 19% respectively. It is not unusual in synthetic control studies that lagged observations of the main outcome receive relatively high weights as past observations often serve as accurate predictors of future observations. With 17% GDP per capita receives the third-highest weight. This makes a lot of sense given the close relationship between GDP per capita and GHG emissions. The relatively low weights assigned to gasoline and Diesel consumption are a bit surprising considering that they should be close predictors of transport GHG emissions. The reason for these small weights might be that gasoline and Diesel consumption is proxied by the lagged emission variables.

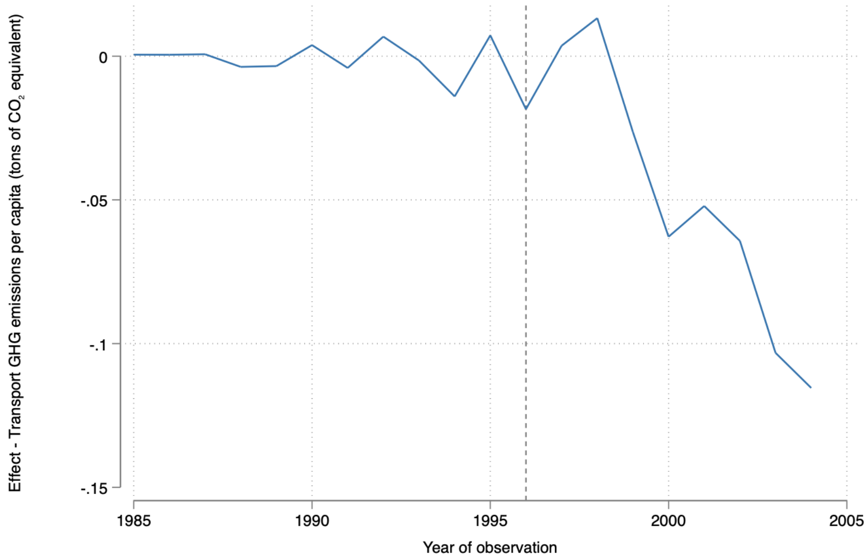
Table 5: Predictor Weights (V-Matrix)

Predictor	Weight
GDP per capita	.17
Urban population	0
Energy use	.06
Gasoline consumption	.05
Diesel consumption	.11
GHG per capita 1985	.43
GHG per capita 1995	.19

Note: The weights do not sum to one due to rounding errors.

The treatment effect is visualized in Figure 5. The depicted line corresponds to the difference in emissions between the synthetic and the actual Philippines from Figure 4. If the gap is equal to zero, the synthetic Philippines perfectly match the GHG emissions from the transport sector in the actual Philippines. The beginning of the fossil fuel subsidy reform in 1996 is marked by a vertical, dashed line. Looking at the graph, one can see that in the first half of the pretreatment period, from 1985 until 1990, the emission gap between synthetic and actual Philippines is quite stable and almost equal to zero. In the second half of the pretreatment period, after 1990, the treatment line starts oscillating a bit more, potentially even with a slight downward trend. This increased oscillation during the second half of the pretreatment phase is an indication that the fit of the synthetic control was slightly better during the first half. Nevertheless, the overall fit during the entire pretreatment period seems relatively good as the treatment line roughly follows a horizontal path oscillating around zero. After treatment occurs in 1996, the path of the treatment line changes noticeably and slopes downwards as the gap between synthetic and actual Philippines widens. At first, the treatment effect is close to zero and is even positive in 1998. One obvious potential explanation for this is that only the second reform attempt in 1998 fully liberalized prices on petroleum products. The first reform in 1996 might have only had a marginal impact. A second potential explanation could be that the Philippines were less affected by the Asian financial crisis than the countries forming the synthetic control. As discussed previously, the per capita emissions of the synthetic Philippines show a small dent in 1997 and 1998, while the per capita emissions of the actual Philippines do not. In any case, the gap between synthetic and real Philippines widens after 1998. The pronounced change in the gap after treatment occurred in 1996 supports the hypothesis that the fossil fuel subsidy reform indeed reduced GHG emissions.

Figure 5: Treatment Effect Synthetic vs. Actual Philippines

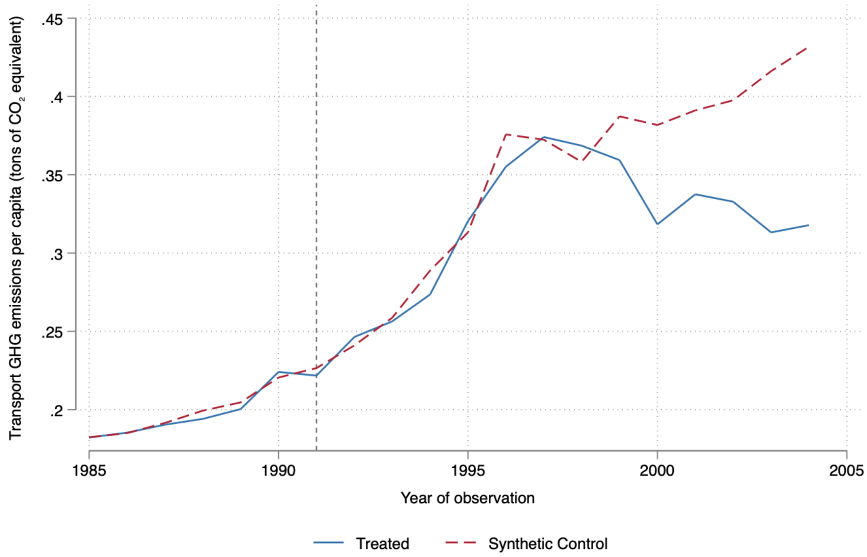


6.2 Robustness Checks

In this section the robustness of the results derived in the previous chapter is tested by carrying out a series of in-time and in-space robustness checks. In addition, a leave-one-out test is conducted to assess to which extent the results are driven by single countries in the donor pool.

As a first robustness check, I carry out an in-time placebo test to assess the robustness of the results across time. To this end, I introduce a hypothetical fossil fuel subsidy reform in 1991, five years prior to the actual reform. Because the reform in 1991 is only a placebo it should have no effect on the synthetic control. I choose 1991 because it is roughly in the middle of the pretreatment phase and still leaves five periods before the placebo treatment occurs to match the new synthetic control. In any case, the results do not appear to be sensitive to the choice of time for the placebo treatment (See Appendix A.6 for a 1993 placebo). The predictor values remain the same as in the main specification but are averaged only over the five years prior to treatment. Furthermore, the lags of the outcome variable are adjusted to 1985 and 1990 respectively. The results of the in-time placebo test are depicted in Figure 6. The synthetic control follows the path of the actual emissions up to 1996, when actual treatment occurred, and diverges thereafter. The placebo treatment in 1991 does not seem to have an impact. The overall fit of the newly generated synthetic control is not much worse than in the main specification.

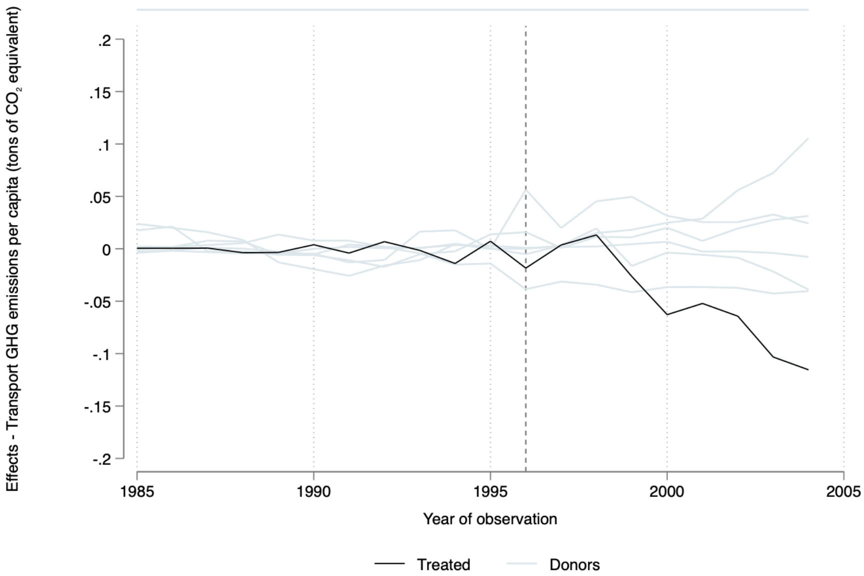
Figure 6: In-Time Placebo Test



Note: Placebo treatment occurs in 1991. Predictor variables are averaged over the pretreatment period 1985-1990. In addition, two lags of transport GHG emissions in 1985 and 1990 are included.

For the second robustness check, I carry out an in-space permutation test. In this test treatment is assigned iteratively to each country in the donor pool and a corresponding synthetic control is constructed. However, because actual treatment only occurred in the Philippines, the treatment effect should be close to zero for the other donor pool countries. Hence, by comparing the treatment effect of the Philippines to the other donor pool countries one can infer whether the effect in the Philippines was unusually large. In this way, in-space permutation tests also allow for the calculation of p-values, which is further discussed and applied to the present analysis in Section 6.3. A problem with in-space permutation tests is that if the synthetic control is not able to replicate the country of interest sufficiently well during the pretreatment period, any gap in the posttreatment period might be more of a sign of a bad fit than a measure of the rarity of the impact (Abadie et al., 2015). A common approach to this problem is to exclude countries with an unsatisfactory Mean Square Prediction Error (MSPE) during the pretreatment period. There are no formal criteria on how to select the threshold above which to exclude countries. In general, the lower the threshold, the higher the matching accuracy, but the more donor countries might have to be dropped. Abadie et al. (2015) propose different thresholds of 20, 5, and 2 times the MSPE of the country of interest. Because of the already small size of the donor pool, I choose a relatively lenient threshold of 10. With this restriction, only Thailand has to be excluded. However, the synthetic control method is not able to produce a convex combination for Malaysia and Bangladesh, which therefore have to be dropped as well. This leaves us with seven countries, including the Philippines, for the in-space permutation test. The results are shown in Figure 7. The effect for the Philippines is the strongest seen over the whole posttreatment period and no other country shows a similar pronounced decline in emissions after 1996. This suggests that the emission reduction in the Philippines did not occur just by chance.

Figure 7: In-Space Permutation Test



Note: Bangladesh, Malaysia and Thailand were excluded because of a pre-treatment MSPE 10 times higher than the Philippines.

The third and last robustness check is a Leave-One-Out test (LOO). This test examines to which extent the results might be driven by a single country making up the synthetic control. This is of special relevance if a single country is assigned a relatively big weight, as is the case with Sri Lanka in the present analysis. The LOO test iteratively excludes one country after the other that received a positive weight from the donor pool and recalculates the new optimal synthetic control with the remaining donors. In the present case, the synthetic control is re-estimated leaving out Indonesia, Malaysia, Myanmar, Sri Lanka, and Thailand one at a time. If the treatment effect is driven by a single country, it will vanish when the respective country is excluded from the donor pool. The results from the LOO test are displayed in a path plot in Figure 8. Figure 9 shows the corresponding treatment effects. As can be seen from the graphs, the effect is not driven by a single country. Even when Sri Lanka, which received a weight of 57%, is excluded from the donor pool, the predicted emissions roughly follow the path of the original synthetic control. The same consequently also holds for the treatment effect. In all specifications of the LOO test the treatment effect remains detectable and of approximately the same magnitude as in the main specification.

Figure 8: Leave-One-Out Path Plot

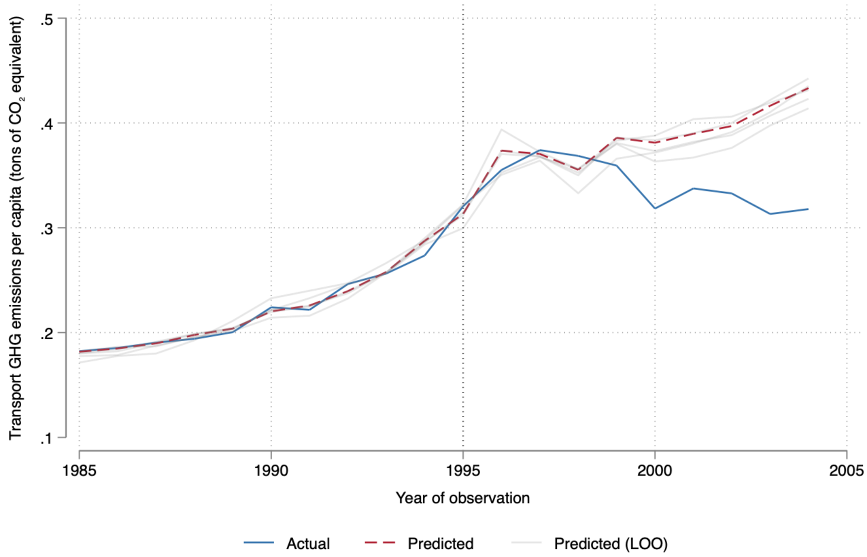
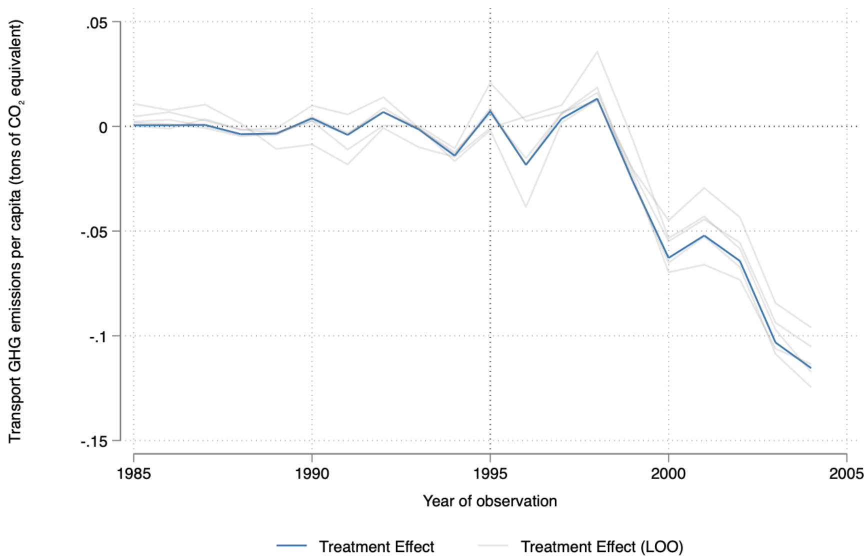


Figure 9: Leave-One-Out Treatment Effect



The three robustness checks carried out above suggest that the results obtained are quite robust. The tests demonstrated that the measured effect is not sensitive to changes in the timing of treatment and is unique to the Philippines in this size. Furthermore, the results are not driven by any single country in the donor pool. The next section discusses how the results obtained from these three robustness tests can be used to calculate p-values for inference.

6.3 Inference

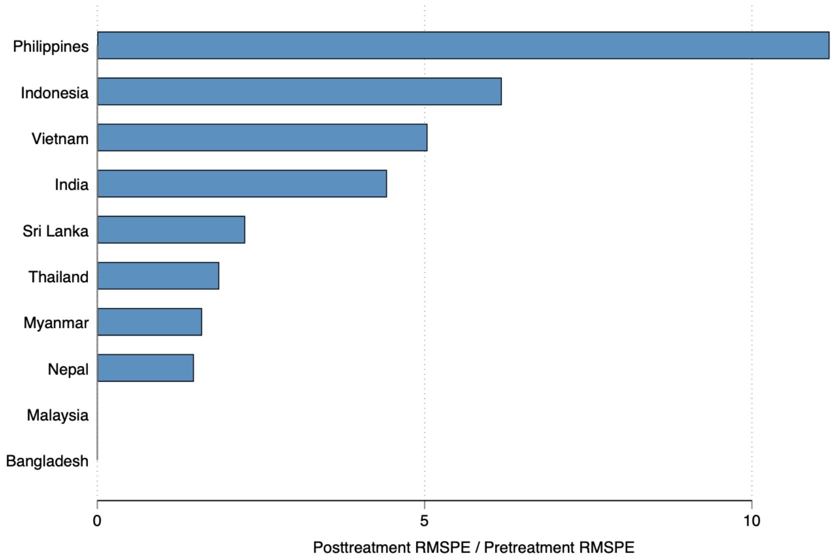
I apply two methods for calculating p-values using the results of the previously carried out in-space permutation test. The first method was proposed by Abadie et al. (2010, 2015) and compares the goodness of fit of all in-space placebos before and after treatment to infer how likely the observed outcome is. The second method presented by Galiani and Quistorff (2017) builds on the first one but calculates p-values for each period by comparing the size of the effect across all permutations.

The first method to calculate p-values uses the results from a permutation test to assess the likelihood that the measured effect happened by chance. More specifically, it compares the ratio of the posttreatment RMSPE to the pretreatment RMSPE obtained from the permutation test across units. In other words, it analyzes the gap between the synthetic control and the actual outcome before and after treatment occurred relative to each other. The reason for looking at the ratio between the pre- and posttreatment period RMSPE instead of just looking at the posttreatment RMSPE is that a high posttreatment RMSPE alone is not indicative of a big effect, because it could also be merely due to a bad fit in the pretreatment period. Another advantage of looking at the ratio instead of the absolute RMSPE is that also countries with a bad fit during the pretreatment period can be included. There is thus no need to set a somewhat arbitrary threshold for the goodness of fit during the pretreatment period. The posttreatment to pretreatment RMSPE ratios for all the donor pool countries are shown in Figure 10. The Philippines stand out as the country with the highest posttreatment to pretreatment RMSPE ratio. The emission gap between the synthetic control and the actual Philippines is about eleven times bigger in the posttreatment period than in the pretreatment period. The country with the next highest ratio is Indonesia with a ratio slightly bigger than half the Philippine ratio. Following Abadie et al. (2015), the p-value for obtaining a ratio as high as the Philippines can now be obtained by calculating the probability of such a result if one were to pick a country at random.[13] In the present case the p-value is thus equal to $1/8 \approx 12.5\%$.[14] Based on this p-value, the results are not statistically significant at any conventional level. However, the p-value obtained by this method is limited by the small size of the donor pool. By construction, 12.5% is the lowest feasible p-value. Therefore, it is possible that the p-value would be lower if fewer countries had to be excluded from the donor pool because of missing data.

[13] The inference method proposed by Abadie et al. (2010, 2015) has received some criticism because the actual treatment is not assigned at random (see e.g., Hahn and Shi (2017)). However, Firpo and Possebom (2018) show using a Monte Carlo simulation that the method performs much better than other comparable inference procedures.

[14] Malaysia and Bangladesh are not included in this calculation because their RMSPE ratio is unknown and could be both higher or lower than the ratio of the Philippines.

Figure 10: Posttreatment to Pretreatment RMSPE Ratio



Note: The RMSPE ratio is zero for Malaysia and Bangladesh because it was not possible to construct a sufficiently good synthetic control for these two countries.

The second method for calculating period-specific p-values is based on Galiani and Quistorff (2017). They calculate two-sided p-values by comparing the size of the effect in each period to the distribution of the effect of the corresponding in-space placebos. In order to account for the goodness of fit, they adjust all effects by their corresponding pretreatment match quality. The exact mathematical calculation is explained in more detail in Appendix A.7. The p-values obtained with this method, calculated using Galiani and Quistorff's software *synth_runner*, are shown in Table 6 together with the absolute value of per capita emissions in the Philippines and the effect size. For the first four periods until 2000, the results are not statistically significant at any conventional level. However, thereafter the p-value is virtually zero meaning that an effect of this size in these periods is highly unlikely to occur just by chance. The results in the final five periods are thus significant at the 1% level.

Table 6: Effect Size and Standardized p-values

Year	Philippines	Effect Size	p-value
1996	0.355	-0.018	0.286
1997	0.374	0.004	0.571
1998	0.369	0.013	0.429
1999	0.359	-0.026	0.288
2000	0.318	-0.062	0
2001	0.338	-0.052	0
2002	0.333	-0.064	0
2003	0.313	-0.103	0
2004	0.318	-0.115	0

Note: Effect size an absolute value of GHG emissions in the Philippines are in tons of CO_2 equivalent per capita.

Considering the two methods to calculate p-values discussed above, it seems unlikely that the measured effect occurred just by chance. While the results do not reach statistical significance under the first method, they are statistically significant at the 1% level using the second method. The difference in significance between the two methods is most likely due to the small sample size limiting the power of the first test. Nonetheless, the inference tests conducted indicate that the detected reduction in GHG emissions did not occur by coincidence.

7 Discussion

The analysis carried out in the previous chapter provides some robust evidence that GHG emissions from transport in the Philippines decreased after the fossil fuel subsidy reform in 1996. Compared to the synthetic counterfactual, emissions per capita were 16% lower four years after the reform and 26% lower nine years after the reform. The magnitude of the emission reduction is thus substantial and comparable in size with the estimates of the emission reduction in transport through carbon taxation by Andersson (2019), Pretis (2022), and Runst and Höhle (2022). A caveat to this comparison is that, in contrast to carbon taxes, the exact relative price increase due to the elimination of fossil fuel subsidies in the Philippines is unknown, and so is the elasticity of carbon emissions with respect to decreases in fossil fuel subsidies. Comparing the results to the predictions in the literature on fossil fuel subsidies, the size of the impact seems to be closer to the earlier, higher estimates of around 6-10% by Burniaux and Chateau (2014) and Schwanitz et al. (2014) than to the latest predictions of 1-4% by Chepeliev and van der Mensbrugghe (2020) and Jewell et al. (2018). However, one should note that these studies estimated the emission reduction potential associated with eliminating fossil fuel subsidies on a global level. The relative emission reduction potential in developing countries like the Philippines, where fossil fuel subsidies tend to be higher compared to developed countries, is naturally higher. Nevertheless, the sizable reduction in transport emissions in the Philippines demonstrates that phasing out fossil fuel subsidies is a functioning tool for lowering GHG emissions. In absolute terms, the elimination of fossil fuel subsidies in the Philippines cumulatively saved a total of 33 million tons of CO_2 equivalent over the nine posttreatment periods.[15] The average annual reduction in emissions was approximately 3.6 million tons of CO_2 equivalent. For comparison, Andersson (2019) finds an average annual reduction in emissions of 2.5 million tons for Sweden, a country roughly eight times smaller than the Philippines but with approximately five times higher per capita GHG emissions. This underlines the high potential for emission reductions in developing countries. Compared to the estimates of the Department of Energy (DOE), the present figures are much higher. The DOE estimates that the OPSF led to additional emissions of 400'000 tons of CO_2 equivalent annually between 1991 and 1995 (Beltran, 2011).[16] Assuming that abolishing the OPSF led to a reduction in emissions of the same size, the emission savings would be equal to approximately 3.6 million tons of CO_2 equivalent over the nine years of the posttreatment period. The present results thus suggest a much bigger reduction in emissions.

[15] Average treatment effect (-0.047 tons of CO_2 equivalent per capita) multiplied by average Philippine population between 1996-2004 (78 million) and number of posttreatment periods (9).

[16] Assuming a conversion rate of nitrogen oxide to CO_2 of 298 (Eurostat, 2022).

With respect to the internal validity, the results are quite resilient. Several robustness checks showed that the results are not sensitive to the model specification and neither are driven by any single donor pool country. Moreover, they are not sensitive to the timing of treatment and show an effect starting only around 1996, even if a placebo treatment is introduced five years earlier. Nonetheless, there are a few other issues that need further discussion.

One drawback of the synthetic control method is that it only reflects overall changes and does not establish a direct causal relationship between treatment and effect. In other words, the results presented in the previous chapter merely state that emissions decreased after 1996 compared to a hypothetical counterfactual, but they do not prove that this reduction was caused by fossil fuel subsidy reform during the same year. The causal attribution of the effect to the reform has to be established through qualitative argumentation. In the case at hand, this concerns the question whether the abolition of the OPSF in 1996 indeed led to an increase in fuel prices, which in turn led to a decrease in GHG emissions. As already discussed in Sections 2.2 and 2.3, there are several facts supporting this narrative. First of all, according to the DOE, between 1990 and 1996 the Philippine government spent more than USD 1.1 billion in today's currency to keep oil prices below market rates (Beltran, 2011; Mendoza, 2014).[17] This is equivalent to 0.8% of total government spending during the same time (Beltran, 2011) and represents a substantial intervention in the domestic oil price-setting mechanism. Second, after the abolition of the OPSF and the associated end of the government's price support for fossil fuels, gasoline prices in the Philippines increased notably stronger than in comparable countries (See Figure 2). This is definitely at least in part due to catch-up effects of artificially held-down domestic prices rising to international levels. For example, between 1999 and 2001, gasoline prices in the Philippines increased by 50% compared to 15-25% in the other countries. It is to be expected that such a big increase in gasoline prices leads to a decrease in consumption and hence also to a decrease in emissions. This interpretation is also supported by the literature. Bernardo and Tang (2008, p. 53) write on this issue: "Today, the public by and large has become desensitized to price adjustments and the full pass-through of increases in world oil prices to domestic pump prices, rather than provoking street protests, have more and more come to be accepted as market realities, eliciting responses in line with textbook consumer behavior—that is, conservation and substitution". According to Mendoza (2014), the increase in fuel price led to a downsizing of vehicles and an increase in less fuel-consuming motorcycles. Consequently, it seems reasonable to attribute the reduction in emissions following 1996 to the fossil fuel subsidy reform beginning in the same year, with fuel conservation and substitution being the two main channels of transmission.

[17] Author's conversion to today's currency using consumer price indices from the World Bank (2022a).

While the above narrative appears convincing, it cannot be ruled out that other factors than the elimination of fossil fuel subsidies contributed to the reduction in transport emissions. It is thus essential to think about other potential confounders that could influence the estimation. One obvious potential confounder could be the 1997 Asian Financial crisis. However, this event was not unique to the Philippines and affected other countries in the region likewise. Consequently, any effect of the Asian financial crisis would be accounted for by the synthetic control. Moreover, robustness tests showed that the results were not driven by any single country. Consequently, even if one of the donor countries was not affected to a similar degree by the financial crisis, the overall results would not change.

The most serious potential confounder is the issue of carbon leakage. Carbon leakage occurs, for example, when consumers in reaction to a carbon tax drive to neighboring countries to refill their cars. The emissions then appear as abated in the statistics of the country of interest, but accrue nevertheless, just in the neighboring countries. Estimating the extent of carbon leakage is extremely difficult and plagues big parts of the research on carbon taxation at least up to some part (Green, 2021). Unfortunately, the present thesis is no exception to this. While classic carbon leakage is no issue due to the Philippines being an island country sharing no land boarder with any other country, the prevalence of fuel smuggling poses a similar problem. Fuel smuggling occurs through the underdeclaration of oil shipments or outright avoidance of customs and tax duties and has been a persistent problem in the Philippines (U et al., 2021). The problem with fuel smuggling is that because smuggled quantities do not appear in any official government record, they are not included in the EDGAR emission database either. Although there exists no data about the size of the issue, experts agree that fuel smuggling is a serious problem, especially because the Philippines are surrounded by countries with notoriously lower fuel prices due to subsidies (Gota, 2014). If the extent of fuel smuggling was unaffected by the reform, any potential effects should be covered by the synthetic control. Yet, whilst the report by the IOPRC (2012) notes that market pricing protects the country from unwanted smuggling, it is more likely that adjusting domestic prices to international levels led to an increase in smuggling from surrounding low-price countries. In this case, the emissions from transport in the Philippines would be underestimated after the reform because emissions corresponding to the fuel consumption in the Philippines would be reported in the country of origin of the smuggled fuels. If such countries form part of the synthetic control, this would also bias the emission counterfactual upwards. In the present study, this could be the case with Indonesia and Malaysia, which together make up 21% of the synthetic control. However, depending on the extent of smuggling, the effect on these countries could be negligible. Nevertheless, the underestimation of emissions in the Philippines combined with a potential overestimation of emissions in the synthetic control could lead to an upwards bias of the treatment effect. In other words, the estimated reduction in emissions is bigger than the real reduction in emissions. Without accurate data on how the quantity of smuggled fuels is reflected in official statistics, it is difficult to make a conclusive assessment of the size of the issue. Yet, there is no indication that a potential increase in fuel smuggling as a result of the reform is big enough that the resulting bias would override the general conclusion, that phasing out fossil fuel subsidies reduced GHG emissions.

Another potential threat to the internal validity could be potential spillover effects of the reform in 1996 to other countries in the donor pool. There is no indication that the reform in the Philippines motivated reforms in other countries. Even if this was the case, countries undergoing a similar treatment have been excluded from the donor pool for exactly this reason. Yet, the change in oil consumption patterns in the Philippines could have other spillover effects. More specifically, the decrease in oil consumption in the Philippines lowers the overall international or regional demand for oil. This could lead to a decrease in world prices, which in turn could spur consumption in other countries. The decrease in consumption in the Philippines could thus theoretically lead to increased consumption in other countries through a temporary decrease in the international oil price. Now, the total oil consumption of the Philippines at the time of the reform in 1996 was equal to less than 0.5% of worldwide oil consumption (BP, 2021). Consequently, it is highly improbable that the reduction in oil consumption in the Philippines affected international oil prices. Any potential spillover effects through this channel should be negligible. A review of the relevant literature revealed no other confounders that are likely to have caused a reduction in oil consumption and emissions of this size. Although the existence of other confounders cannot be ruled out with certainty, by lack of objection it can be assumed that the 1996 fossil fuel reform indeed caused the estimated reduction in emissions.

In summary, the results of the present thesis withstand all the standard robustness tests and seem quite resilient. However, the unknown increase of fuel smuggling as a consequence of the 1996 reform poses a risk to the internal validity of the present study, potentially causing an overestimation of the emission reduction. Nevertheless, this study is one of the first to present empirical ex-post evidence of the emission reduction potential associated with phasing out fossil fuel subsidies. With respect to the external validity, the results should be interpreted with caution. As Burniaux and Chateau (2014) argue, the effect of phasing out fossil fuel subsidies is very heterogeneous across countries and regions. The emission reduction potential depends on the type and size of subsidies as well as the social and political context of each country. Furthermore, the fossil fuel subsidy reform in the Philippines was followed by a strong increase in international oil prices. The emission reduction might have been smaller in a scenario with stable or even decreasing world oil prices. The strength of the effect is thus dependent on the context. Nonetheless, the present thesis offers some encouraging evidence for other countries to eliminate environmentally harmful fossil fuel subsidies as part of their strategy to fight climate change. This is especially true considering the additional positive fiscal and distributional effects of phasing out these subsidies.

8 Conclusion

In order to limit global warming to 1.5°C by the end of the century, rapid and immediate large-scale reductions in greenhouse gas (GHG) emissions are needed. The present thesis aimed to answer the research question, whether phasing out fossil fuel subsidies on petroleum products reduces GHG emissions, and provides some first empirical ex-post evidence from the 1996 fossil fuel subsidy reform in the Philippines. By constructing a synthetic counterfactual from a pool of donor countries that mimics the actual Philippines in every aspect, but where the 1996 subsidy reform did not take place, I am able to isolate the effect of phasing out fossil fuel subsidies on emissions from transport. The results suggest that due to the elimination of fossil fuel subsidies, per capita emissions from transport were 16% lower four years after the reform and 26% lower nine years after the reform, compared to the synthetic counterfactual. In absolute terms, the elimination of fossil fuel subsidies in the Philippines cumulatively saved a total of 33 million tons of CO_2 equivalent over the nine posttreatment periods. The results are statistically significant at the 1% level and are robust to all standard robustness tests from the synthetic control literature. A limitation of the present analysis is the unknown extent of fuel smuggling in the Philippines. If fuel smuggling increased as a result of the fossil fuel subsidy reform, the overall results might be overestimated. However, it is unlikely that the arising bias is big enough to overrule the overall conclusions.

The present thesis contributes to the existing theoretical literature by offering some first empirical evidence that removing fossil fuel subsidies reduces GHG emissions from a real-world case study. Moreover, the present study adds to the growing literature on carbon taxation using the synthetic control method by extending the research to the field of negative taxes, i.e., subsidies. The analysis in the present paper shows that the synthetic control method is a suitable and powerful methodology to study the environmental effects of fossil fuel subsidies. However, much more empirical research is needed to better understand the impact of removing fossil fuel subsidies on GHG emissions. With respect to the present thesis, future research could try to quantify the extent of fuel smuggling to provide more accurate results on the emission reduction potential. Another interesting path for future research could be the analysis of similar reforms in other sectors. More generally, future research could focus on estimating the elasticity between subsidies and emissions and different channels of transmission.

To conclude, the present thesis provides some first empirical evidence that phasing out fossil fuel subsidies reduces greenhouse gas emissions. While the results are not directly applicable to other countries, they offer encouraging evidence for policymakers all around the world to evaluate the role of fossil fuel subsidies in the fight against climate change.

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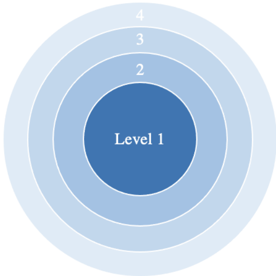
A Appendix

A.1 Defining Fossil Fuel Subsidies

This section aims to provide a brief overview of the different definitions of fossil fuel subsidies used in the literature and by international organizations. As their name suggests, fossil fuel subsidies refer to subsidies to non-renewable energy sources. However, a quick survey of the literature reveals that over the years several competing definitions of what constitutes a subsidy have emerged (Sovacool, 2017; UNEP, 2019). These different definitions are briefly presented and discussed in the following.

The simplest way to explain the different definitions of fossil fuel subsidies is through a framework consisting of four concentric circles developed by the Organisation for Economic Co-operation and Development (OECD, 2010). An adapted version of the framework by Gerasimchuk et al. (2017) is depicted in Figure A.1. The innermost circle represents the simplest form of subsidies: Direct transfers to consumers or producers. This includes also other financial assistance such as loan guarantees, credit lines, or the provision of other preferential access to financing. The next bigger category widens the definition and includes also foregone government revenue due to tax exemptions or reductions on energy production or consumption. On the consumer side, this refers to the exemption of energy products from different consumption taxes such as value-added taxes (VAT) or goods and service taxes (GST). On the producer side, this covers foregone government revenue due to the provision of public services below market price or the purchase of energy products above market price to support private companies. The third circle broadens the definition further and incorporates also transfers induced by government regulation, even if there is no direct financial transfer. Depending on the definition, this category can also include cross-subsidies from one consumer group to another. The fourth and last circle provides the most ambitious and probably also the most controversial definition. It benchmarks energy taxation to regional levels and considers lower than average taxation as a subsidy. Moreover, it classifies any level of taxation below the socially optimal rate as a subsidy.

Figure A.1: Concentric Circles of Energy Subsidy Definitions



Level	Consumer Energy Subidy	Producer Energy Subsidy
1	Direct transfers or potential direct transfers of funds to consumers	Direct transfers or potential direct transfers of funds to producers
2	Energy fully or partially exempt from VAT, GST and excise tax on consumption	Government revenue forgone (reduced and exempt tax rates) Government provided or purchased goods and services (above or below market prices)
3	Price controls, including cross-subsidies: energy sold below the cost of production, imports and international benchmark price to certain categories of consumers	Income or price support (above market rate prices for producers such as feed-in tariffs)
4	Energy exempt from social cost of externalities (non-internalized externalities) Energy sold below regional or international tax levels	Government tax and regulation levels below regional or international levels

Note: Based on Gerasimchuk et al. (2017) and OECD (2010).

The framework presented above helps to understand the differences in the various definitions of fossil fuel subsidies applied by international organizations. The most widely accepted definition is from the World Trade Organization's (WTO) agreement on subsidies and countervailing measures, which was signed by 164 countries (Gerasimchuk et al., 2017). In this agreement, subsidies are generally defined as any financial contribution by a government or public body that conveys a benefit to a beneficiary (WTO, 2006). In practice, however, the definition of the WTO finds only limited application because of its trade-related focus (Gerasimchuk et al., 2017). A more widely used definition comes from the IEA, which defines energy subsidies as "any government action directed primarily at the energy sector that lowers the cost of energy production, raises the price received by energy producers, or lowers the price paid by energy consumers" (IEA, 2014, p. 315). The OECD applies a relatively similar definition. It defines an energy subsidy as "any measure that keeps prices for consumers below market levels, or for producers above market levels or that reduces costs for consumers or producers" (OECD, 2005, p. 114). The main difference between the IEA and the OECD lies in their respective approaches to measuring and quantifying energy subsidies (Grigonyte & Barany, 2015). The most comprehensive definition, spanning all four circles, comes from the IMF, which makes an additional distinction between pre- and post-tax subsidies. Pre-tax subsidies roughly correspond to the common definition of fossil fuel subsidies, as applied by the IEA and the OECD. Post-tax subsidies refer to the difference between actual prices and what prices would look like if supply costs and environmental externalities were fully accounted for (Coady et al., 2019). These two types of subsidies are sometimes also referred to as explicit and implicit subsidies (Parry et al., 2021).

A.2 Measuring Fossil Fuel Subsidies

Because of their wide scope and intricacy, as well as their intertwining with other policies, fossil fuel subsidies can be ubiquitous yet hard to pin down (Sovacool, 2017). Generally, the systematic tracking and measurement of energy subsidies has only gained widespread attention from policymakers fairly recently (Kojima & Koplow, 2015). As a result, detailed data on different fossil fuel subsidies is often not available, especially for earlier years (Couharde & Mouhoud, 2020). This section aims to shed light on the challenges associated with measuring the size of fossil fuel subsidies. To this end, it presents the three main methods applied by international organizations and highlights their differences.

The IEA, the OECD, and the IMF all collect data in a systematic way, although using slightly different methodologies (Grigonyte & Barany, 2015). The IEA applies the so-called ”price-gap” methodology. The price-gap method is one of the most common approaches to measuring fossil fuel subsidies and has been used in the literature for a long time (e.g., Coady et al. (2010), Kosmo (1987), and Larsen and Shah (1992)). It quantifies the size of a subsidy by comparing the domestic end-user price of a product with an international reference price (IEA, 2022). If the difference is positive, i.e., the domestic price is lower than the reference price, the fossil fuel is considered subsidized. The total size of the subsidy can then be calculated by multiplying this price gap with the total quantity consumed of a good. A drawback of price gap estimates is that they are highly sensitive to the reference price, which is calculated as the price of a product at the nearest international trading hub, adjusted for transportation, quality, insurance, and marketing costs plus VAT (IEA, 2022). As a result of this, subsidy estimates using the price gap method can vary greatly with international prices from year to year because of the fixed price regimes, which are still in place in many countries (Grigonyte & Barany, 2015). Moreover, as Gerasimchuk et al. (2017) note, by focusing entirely on prices, the definition used by the IEA disregards any subsidy without a necessary direct impact on market prices, such as, tax exemptions. In order to avoid these pitfalls, the OECD's inventory approach does not rely on prices. It measures fossil fuel subsidies directly in the government budgets, creating an inventory of all support measures in place, which ideally includes direct transfers, foregone government revenue due to tax breaks as well as other forms of support, such as the preferential provision of financing or insurance (Sovacool, 2017). Hence, while the IEA approach is less resource-intensive to compute, the OECD method also captures subsidies without a direct impact on prices. Grigonyte and Barany (2015) conclude that OECD and IEA estimates cannot be directly compared and should rather be seen as complements to each other, where the OECD approach is preferable for advanced countries and the IEA's method is better suited for developing countries. Lastly, the IMF builds on the IEA's price gap method for the calculation of pre-tax subsidies, but adds the cost of non-internalized externalities on top for the estimation of post-tax subsidies. (Grigonyte & Barany, 2015). The calculation of these externality estimates is thereby quite sensitive to the underlying assumptions, which is one of the reasons why the OECD and the IEA decided to not include them in their estimates (Gerasimchuk et al., 2017). Because of the inclusion of externalities, IMF estimates of the size of global subsidies are usually substantially larger (Grigonyte & Barany, 2015). The different definitions and estimation methods discussed in the present and the preceding chapter are summarized in Table A.1.

Table A.1: Fossil Fuel Subsidy Definitions and Estimation Methods

Organization	Method	Definition	Strengths	Limitations
IEA	Price-gap approach	Government action that lowers the cost of production, raises the price received by producers or lowers the price paid by consumers	Less data intensive, good indicator of price distortions	Sensitive to assumptions on reference price, ignores subsidies without effect on prices
OECD	Inventory approach	Government measure that keeps prices for consumers below market levels, or for producers above market levels or that reduces costs for consumers or producers	More holistic measurement of support, can reveal separate effects on producer and consumer markets	Data intensive, and empirical data for many markets remains limited
IMF	Price-gap and inventory approach	Pre-tax: Price paid by consumers below a benchmark price, producers above the benchmark; Post-tax: Pretax plus cost of unaccounted externalities	Includes broader social, environmental, and economic impacts	Externalities are difficult to monetize, also data-intensive and prone to very large variations in estimates

Note: Adapted from Couharde and Mouhoud (2020) and Sovacool (2017).

A.3 The Size of Fossil Fuel Subsidies

This chapter presents different estimates on the size of fossil fuel subsidies worldwide and highlights the most important points of the international policy discussion of the past years.

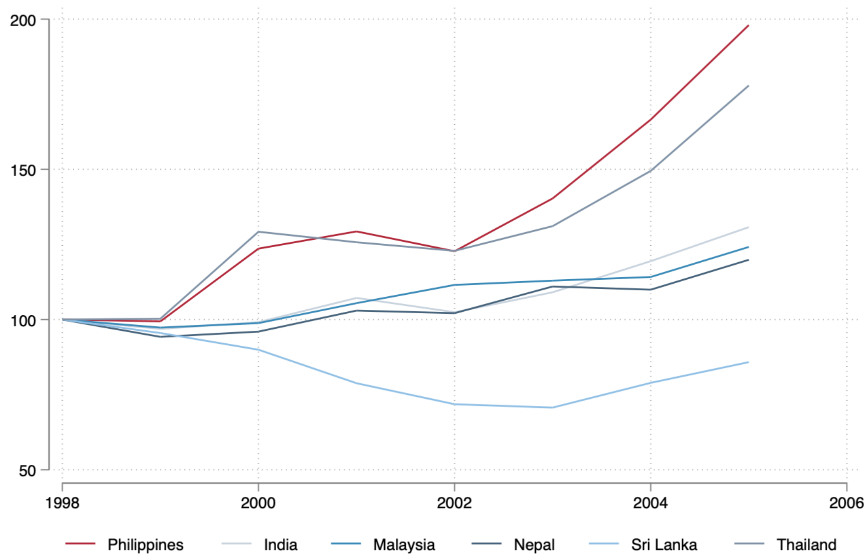
The most recent estimates on the size of global fossil fuel subsidies in 2020 range from USD 178 billion by the OECD (2021) to USD 5.9 trillion by the IMF (Parry et al., 2021). The sizable difference is thereby due to the fact that the IMF includes the cost of externalities associated with the consumption of fossil fuels, while the OECD does not. Nonetheless, even considering only pre-tax subsidies, i.e., undercharging for supply costs and producer subsidies, the IMF estimates worldwide fossil fuel subsidies still at USD 450 billion (Parry et al., 2021). A caveat to the comparison of the two estimates is that the OECD's inventory approach only covers 50 countries, mainly pertaining to the OECD and the G20, whilst the IMF covers 191 countries. The IEA, on the other hand, covers 41 emerging and developing countries, including China and India, and estimated fossil fuel consumption subsidies at USD 180 billion in 2020, the lowest value since the beginning of measurement in 2007 and 40% lower than in 2019 (IEA, 2022). However, the IEA notes that this drop was mostly due to an overall drop in energy use and fossil fuel prices during the same year. In 2021, fossil fuel subsidies jumped back to USD 440 billion (IEA, 2022). The volatility in the IEA's estimates exemplifies the dependence of the price gap approach on international prices.

Compared to studies from previous years, current estimates of the total size of global pre-tax fossil fuel subsidies are higher. Because of the differences in methodology, this can be best illustrated by comparing different studies over time carried out by the same organization, say the IMF. The first comprehensive study by the IMF estimated global pretax subsidies in 2011 at USD 492 billion, or 0.7% of global GDP (Clements et al., 2013). A follow-up study two years later estimated global subsidies in 2011 slightly higher at USD 523 billion and projected them to decrease to USD 333 billion by 2015 (Coady et al., 2015). The slightly higher estimate is at least in part due to some methodological refinements and wider country coverage. In an update in 2019, Coady et al. (2019) note that global pre-tax subsidies declined notably due to decreasing international fuel prices and were around USD 269 billion in 2016. Finally, the most recent study by the IMF puts global pre-tax subsidies in 2020 up at USD 450 billion again (Parry et al., 2021). The estimates are higher than in previous studies by the IMF due to further improvements in methodology and country coverage, but also because of rising fuel prices. Noteworthy, subsidies on Diesel and gasoline represent the second and third biggest subsidy category by end-user, representing 19% and 12% of global subsidies (Parry et al., 2021).

A.4 Indexed Gasoline Prices Adjusted for Inflation

Figure A.2 shows annual, inflation-adjusted gasoline prices in the Philippines and comparable countries, indexed at one hundred in 1998. As discussed in Section 2.3, oil prices are a major driver of inflation. Any increase in inflation due to the 1996 subsidy reform should thus be included in the analysis of the effects. Nevertheless, even when adjusting for inflation, the Philippines show a stronger increase in prices than most other countries, with the exception of Thailand, which also had comparatively liberalized oil pricing during that time.

Figure A.2: Indexed Inflation-Adjusted Gasoline Prices

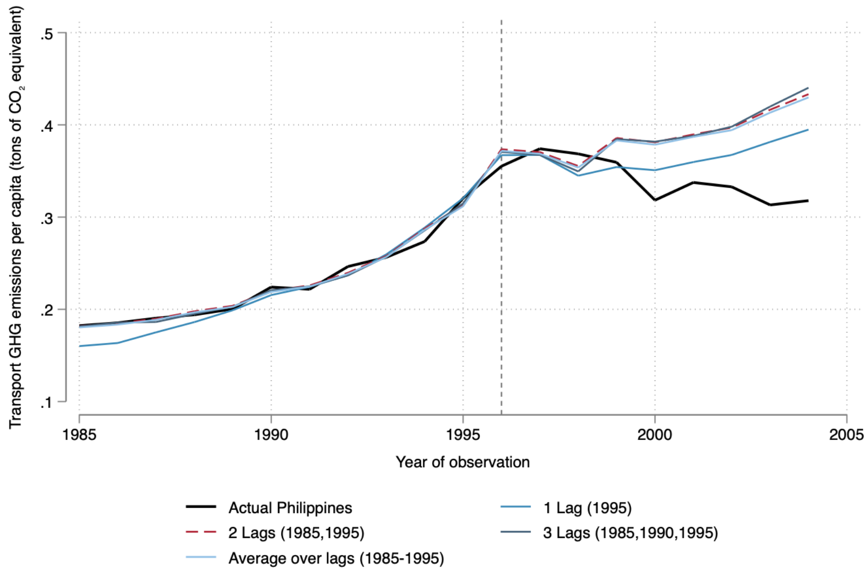


Note: Gasoline prices are inflation-adjusted yearly averages, indexed at one hundred in 1998. Consumer price indices were obtained from the World Bank (2022a) and price data from Kpodar and Abdallah (2017)

A.5 Main Results for Specifications with Various Outcome Lags

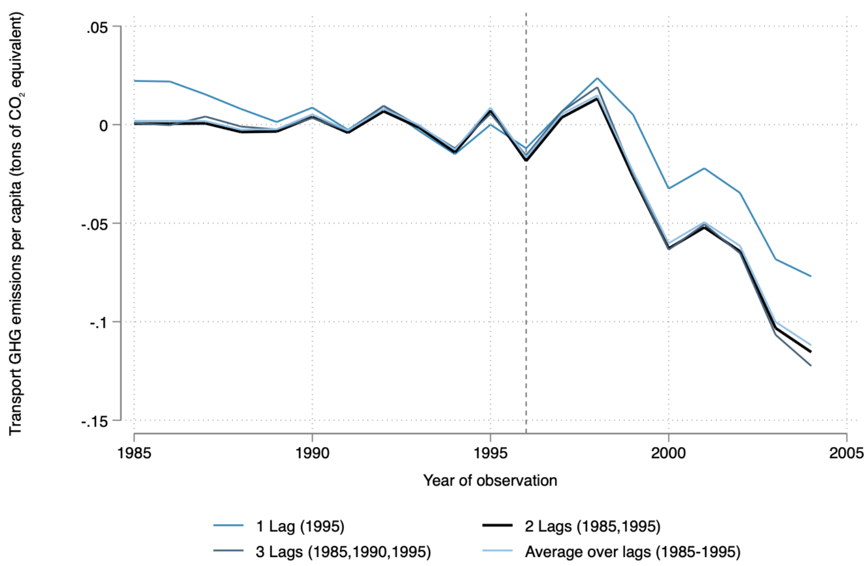
The following two graphs show the sensitivity of the results to changes in the selection of the lagged outcome variables. Figure A.3 shows the fit of the synthetic control for various specifications. Figure A.4 shows the treatment effect for the same specifications. As can be seen from the graphs, the results are not sensitive to the selection of outcome lags with the exception of the specification with only one lag, which also has a substantially worse pretreatment fit.

Figure A.3: Path Plot Various Lags



Note: Predictor variables are averaged over the period 1985-1995.

Figure A.4: Treatment Effect Various Lags

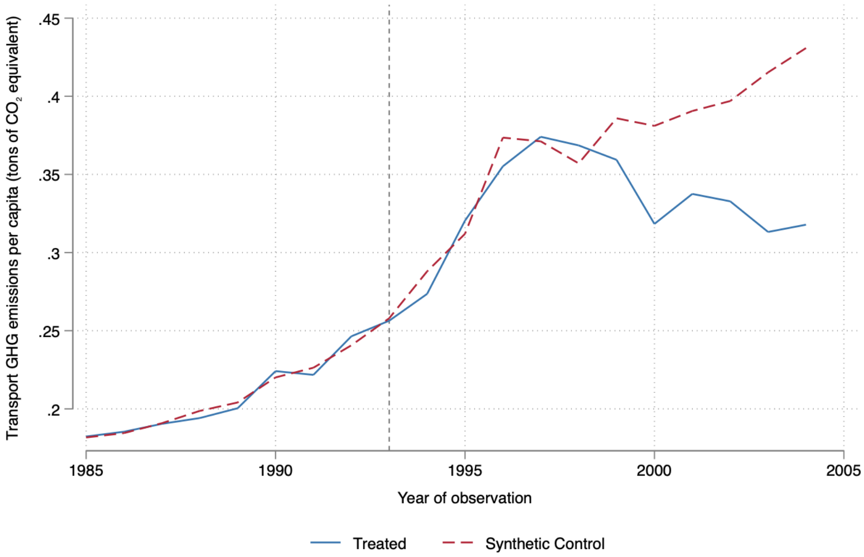


Note: Predictor variables are averaged over the period 1985-1995.

A.6 In-Time Placebo Tests

Figure A.5 below shows the results of an in-time placebo test, where a hypothetical treatment occurred in 1993. As can be seen, the results are very similar to the 1991 in-time placebo test in Figure 6.

Figure A.5: In-Time Placebo Test



Note: Placebo treatment occurs in 1993. Predictor variables are averaged over the pre-treatment period 1985-1992. In addition, two lags of transport GHG emissions in 1985 and 1992 are included.

A.7 Two-Sided *p*-values

This section explains the calculation of period-specific two-sided p-values as presented by Galiani and Quistorff (2017) in more detail. While there exists also a method to calculate one-sided p-values, their calculation is not discussed here because the present paper only uses the two-sided version. For more information on one-sided p-values please refer directly to the Galiani and Quistorff paper.

Assume the estimated effect for the treated unit $j = 1$ in period t is defined as $\hat{\alpha}_{1t}$. The distribution of the respective in-space placebos can then be obtained from a permutation test and is equal to $\hat{\alpha}_{1t}^{PL} = \{\hat{\alpha}_{jt} : j \neq 1\}$. The two-sided p-value is then given by

$$p\text{-value} = \Pr(|\hat{\alpha}_{1t}^{PL}| \geq |\hat{\alpha}_{1t}|) = \frac{\sum_{j \neq 1} 1(|\hat{\alpha}_{jt}| \geq |\hat{\alpha}_{1t}|)}{J}$$

This is equal to classical randomization inference if treatment is assigned at random. However, even if treatment is not randomized the p-value can still be interpreted as the proportion of control units with an estimated treatment effect larger or equal to the treated unit. In order to account for the varying goodness of fit of the synthetic controls during the pretreatment phase, Galiani and Quistorff (2017) adjust all the estimated effects $\hat{\alpha}_{jt}$ by dividing them with their respective pretreatment RMSPE to obtain the standardized p-values, which are used in the present paper.