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Electricity Certificate Scheme as an Incentive for Renewable Energy Development in Norway

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Electricity Certificate Scheme as an Incentive for Renewable Energy Development in Norway

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This thesis is a part of the MSc programme at BI Norwegian Business School. The school takes no responsibility for the methods used, results found and conclusions drawn.

Abstract

This study empirically examines the efficacy of the Electricity Certificate Scheme to renewables energy development in Norway. We construct monthly electricity production panel data from various renewable-based sources for Norway and other European countries between 2004 and 2019. By employing the difference-in-difference method, we find the real positive effect of the Electricity Certificate Scheme on renewable-based electricity production on hydroelectricity in Norway, which has been further reinforced by deploying synthetic control methods in the European hydroelectricity production level. The real effect of the Electricity Certificate Scheme on wind-based electricity production in Norway is inconclusive. We therefore conclude that the Electricity Certificate Scheme has a positive impact on certain types of renewables development in Norway.

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List of Abbreviations and Acronyms

BLUE	Best Linear Unbiased Estimators
CO2	Carbon Dioxide
DiD	Difference-in-Differences Analysis
ECM	Entities in Charge of Maintenance
EEA	European Economic Area
EU	European Union
FIT	Feed-in Tariff
GCC	Green Current Certificate
GDP	Gross Domestic Products
GHG	Greenhouse Gases
GWh	Gigawatt-hour
HAC	Heteroskedasticity and Autocorrelation Consistent Covariance
KTOE	Kilotonnes of Oil Equivalent
kWh	Kilowatt-hour
MSPE	Mean Squared Prediction Error
MW	Megawatt
MWh	Megawatt-hour
NOK	Norwegian Kroner
NOx	NVE ELspot region “x”
NVE	Norwegian Water Resources and Energy Directorate
OLS	Ordinary Least Squares Regression
PV	Photovoltaic Solar Panel
TGC	Tradable Green Certificate
TGC-M	The Norwegian - Swedish Electricity Certificate Market
TWh	Terawatt-hour
UK	The United Kingdom

1 Introduction

Resulting from the expansion of human populations and activities, CO2 emissions have increased by about 90% whilst emissions from combustion of fossil fuels (such as oil, gas and coal) and industrial processes contributing about 78% to total greenhouse gas (GHG) emissions increase from 1970 to 2011 (EPA, 2017). This trend in global emissions is at a much faster rate than natural processes alone and brings the impact of "global warming", the major driving factor in man-made climate change (UNFCCC, 2007).

Global warming is likely to present new, unpredictable challenges like extreme weather and climate events (Næss, 2005) which may cause damages to the societies. In Norway, snow and flooding patterns might be altered due to global warming and have serious implications for local societies. For example, the 1995 floods in two municipalities in South-eastern Norway damaged infrastructure and farmland, partly due to high snow accumulation but more importantly to the late onset of the snow melting combined with rapid temperature increases and sudden heavy rainfall (Eikenæs, Njøs, Østdahl & Taugbøl, 2000).

Despite the negative consequences of human-induced climate change, demand for energy and services that are environmentally associated is increasing because of the social and economic development in all societies since industrialisation revolution in the 1850 (IPCC, 2011). According to the statistics (IEA, 2019), total final consumption by fossil fuel globally in 2017 is 6,524,845 KTOE (Kilotonnes of Oil Equivalent), which is 50% more than the number in 1990. In Norway, the ratio of total final consumption by fossil fuel in 2017 compared to the number in the year 1990 (8,137 KTOE) is 1.10 times.

GHG resulting from the demand and services, where fossil fuels accounts for the majority of global anthropogenic emissions, will likely cause global warming - the major aspect of climate change (IPCC, 2007). In order to mitigate the climate change, it is necessary to find options to lower GHG emissions from the energy and other services while satisfying the demand for those sectors. Based on the AR4 assessment (2007), renewable energy and fuels, as one of the options, have the large potential to mitigate climate change whilst providing wider profits.

Hydropower, wind and thermal are three of the principle types of renewables (Boyle, 2012). In Norway, 120 – 135 TWh of renewable energy is produced annually between 2000 and 2011. Electricity produced from other renewables accounts for 1 to 5%, which is a negligible number compared to the 95 to 99% of electricity produced by hydropower (SSB, 2012). Hydropower covers almost all the domestic consumption of electricity with almost no GHG emission.

Although hydro can cover the domestic consumption of electricity, fossil fuels can be replaced by other renewables in the offshore petroleum extractions, road transportation and heating sector, which account for at least 45% of the GHG emissions in 2011 in Norway. The fact sheet demonstrates that Norway has abundant water power and wind resources (Norwegian Environment Agency, 2015). Therefore, Norway is an ideal country for the development of hydro and wind power. Meanwhile, as a member of the European Economic Area (EEA), Norway needs to implement 67.5% share of renewable energy in gross final energy consumption (applies to consumption of electricity, heating/cooling and transport since December 2011), which is a directive made by the EEA Joint Committee (Energifakta Norge, 2018). Based on the aforementioned fact, Norway has both much potential and necessity to promote energy from hydro, wind and thermal power with regional focus.

There are two reasons why incentive schemes are necessary to the development of renewables. Firstly, the decisions of renewable investments are affected by incentive policies. According to the posit made by Masani and Emanuela (2013), rational evaluation of the economics of the investment opportunities, public support (under the form of incentive schemes, taxation or other governmental expenditure), knowledge and confidence in technological adequacy are the factors that affect the decisions of renewable investments. Drahokoupil (2013) defines investment incentive as a “government-implemented incentive policy”. If Masani and Emanuela’s posit is correct, incentive schemes would be necessary in order to promote the investment of the energy generation from renewables. To be more specific, the government implements investment incentives that encompass measurable economic advantages to renewable enterprises to steer investment into renewable sectors or regions.

Secondly, investment incentives can mitigate climate change and promote renewables development. According to Fischer and Newell's introduction (2005), investment incentives (such as generation subsidies for renewable energy, cost reduction of research and development and tax credit) can help to reduce greenhouse gas emissions from emitting energy sources and promote technological development and renewables diffusion.

There are different incentive schemes in different sectors. In the renewables sector, Menauteau (2003) indicated that quota systems (tradable green certificates, "TGC"), bidding systems (auctions), or schemes with focus on prices (Feed-in tariffs, "FITs") are the incentive schemes used for producing electricity from renewable sources. Menauteau concludes that the FIT scheme is more efficient than a bidding system. However, knowledge of these three incentive schemes in the renewables sector is not comprehensive. The accurate FIT rate is unknown to the government. This is because the real cost of production is also unknown to the government, which might risk the setting of FIT rate that is either too high or too low (OECD, 2017). Pricing of renewables-based electricity through auction might not reflect the actual value of the electricity itself. Even though the policymakers seek to procure renewables-based electricity at the lowest price through the use of auctions, the actual values of the electricity to the different bidders are unknown but correlated (Mcafee & Mcmillan, 1987). Menauteau (2003) also highlights that the efficiency of green certificate trading in the theoretical interest is unknown and must be confirmed through practice.

In 2015, the green tax commision ("grønn skattekommisjon") recommended a combination of tax of natural resources and economic support to the development of environmental technology. This combination could indirectly deduct the cost of investment to the renewable projects so it can be seen as an investment incentive scheme. However, we did not find the corresponding change from the open sources up to date and therefore it cannot be analysed. Under the Energy Act, it is noteworthy that taxes to income, natural resources, concession, energy, grid and output are in place as non investment incentive schemes in the energy sector which might support renewables-based electricity production in Norway (Ministry of Petroleum and Energy, 2016). Since Norway pursues its goal for producing

67.5% electricity from renewables in 2020, and it had neither auctions (IRENA, 2013), nor FIT or production-based support scheme as investment incentive schemes (Inderberg, Kerstin & Britta, 2018). Therefore, only the efficacy and efficiency of the quota systems to renewables development can be evaluated.

Norway and Sweden founded a joint green certificate market in 2012, with expected results of 28.4 TWh (26.4 TWh was amended 1st January 2016) of new renewable energy production by 2020. According to various databases from NVE, some new and existing wind and hydro projects have been given concessions to get under way or expand their current capacity. Statement from Energifakta Norge (2019) shows that 3.4% of Norwegian electricity production capacity is generated by 33 wind farms, which accounts for a moderate share of production capacity. The production of electricity from renewable sources such as hydro, wind and solar power plants has also increased to a great extent.

We believe that there are numerous critiques existing upon the implementation of a tradable green certification (TGC) scheme. To begin with, the efficacy of the TGC scheme is being questioned. Bye and Hoel (2009) put the conditions in the Norwegian energy market and the low price in the certificate market into consideration then unfavourably conclude that TGC would be a scheme that does not show the anticipated effect for the energy market and the climate and that are expensive and pointless. We also consider whether TGC is a neutral investment incentive scheme to all kinds of renewables. By evaluating theoretical models and empirical evidence on the effects of different schemes, Popp (2019) suggests that technology neutral schemes can favor one technology over another in his working paper. On the same line of thought, Johnstone, Haščič and Popp (2010) compare different incentive schemes to find that TGC favors development of wind energy.

The most supporting findings are from De Grotte and Verboven (2019), who calculate that Green Curren Certificates (GGC or the equivalence of the Electricity Certificate Scheme in our thesis) is the main source of benefits that increase the present value of future benefits of solar panel (PV) systems in the short-term only. The upfront investment cost of a PV system eventually equals net metering when GCC dies out in seven years. Their findings indicate that the generous GCC scheme can provide incentives to the development of renewables in the short-term and suggest that an even faster adoption of PV systems can be led if consumers would have been more forward-looking.

Based on the available data on the production of renewable energy and the literature, our main question arises: Does the introduction of the Electricity Certificate Scheme have a positive effect on the production of renewables in Norway? We adopt the difference-in-differences (DiD) analysis to extract the real effect of the Electricity Certificate Scheme implementation among other influential variables. We also derive the impact of the Electricity Certificate Scheme at the international level by adopting the synthetic control method.

The Electricity Certificate Scheme has the fundamental characteristics of an "event" with pre- and post-treatment timespans, and these two quantitative methods are well-established for event study. In addition, methods of DiD and synthetic control have been successfully deployed regarding literature concerning environmental policies. Both DiD and synthetic control methods are applied to the collected time series and panel data of renewable energy output respectively to answer the main question. By deploying these two methods, we found that the Electricity Certificate Scheme appears to have a positive impact on the production of hydro power but not wind power in Norway.

In order to derive the influence of the Electricity Certificate Scheme on the ongoing development and operation of renewables of Norway, variables impact on new production and capacity of renewable-based electricity have been analysed through the auxiliary concession analysis. We found that there is a significant increase in new production and capacity of renewable-based electricity in Northern Norway under the said scheme.

This thesis is organized as follows. It first illustrates the literature grounds of our research interest in section 2 and introduces the Norwegian – Swedish Electricity Certificate Market in section 3. The thesis describes collected and analysed datasets in section 4. It then introduces the adopted methods in section 5 and explains the main results in section 6. The deployed auxiliary concession analysis, its findings and potential extensions of our thesis will be revealed in section 7. Last but not least, remarks of conclusion are presented in section 8.

2 Literature Review

As mentioned in the introduction, Norway has a necessity to promote renewables with regional focus by deploying TGC, one type of investment incentive schemes in the renewables sector. However, little consensus regarding the efficacy of investment incentive has emerged. Some experts have argued that incentive policy is just one of the many factors that influence the success of investment, as well as there is insufficient evidence to show incentive policy is an effective tool to boost the investment. Others have claimed that incentive policy has contributed to the rapid growth of developing countries. Based on these arguments, James (2009) concludes that states that efficacy of investment incentives is based on the sector and level of development involved.

Although Norway uses neither auctions nor FIT as investment incentives to develop renewables, we would still review the articles of auction systems, FIT, in addition to the focal TGC, all of which have been designed to stimulate development in renewables. We will also highlight TGC and its comparison with FIT.

FIT is an economic policy which the government and renewable-based electricity produces into contracts with grid access, long-term time frame and cost-based purchase prices provisions. This scheme could encourage the diversity in renewables development additionally (IRENA and CEM, 2015). Moreover, as defined by IRENA's report, renewables auctions are procurement auctions whereby the government first issues a call for tenders (mainly consist of renewable project developers) to install an project with amount of capacity of renewable-based electricity, and then evaluates the bid offered by tenders with a price per unit of electricity which tenders are able to finish the project on the basis of the price and criteria.

TGC is a tradable asset which proves that electricity has been generated by renewables. The main objective of TGC is to encourage the penetration of electricity generation based on different renewables into the electricity market, with equal terms to each renewable without involving direct fiscal subsidies. Amundsen and Bergman (2012) explain that generators of electricity based on renewable-based electricity obtain an amount of TGC in related to the amount of renewable-based electricity and get the revenue from selling both the electricity and the TGC to the consumers and companies that are required to buy certificates to a certain amount of the consumption of electricity. Price of TGC is determined by the supply and demand of renewable-based electricity in the market.

According to the experiences from a number of European countries, Fouquet and Johansson (2008) finds that the TGC system is less effective and efficient than maintaining a national FIT system because FIT delivers larger and faster penetration of renewables compared with TGC with lower costs. Haas et al. (2011) have two findings that there is a low effectiveness of TGC with respect to electricity from renewables deployment of less mature technologies, as well as the intrinsic stable FIT system appears to be a key element for achieving the success of the goal. Canton and Lindén (2010) conclude that TGC is a suitable support instrument once the volumes of renewables have an impact on the internal market. In other words, support schemes should fit the level of development of the renewable's technology as well as its shares on the internal market. Based on the findings and conclusions from diverse articles, we understand that it is difficult to say whether TGC, auction systems, and FIT is the best scheme used to develop electricity production from renewables in Europe.

As mentioned before, promotion of renewable-based electricity has been based on three schemes: FIT, TGC and auction systems. Nielsen and Jeppesen (1999) argue that TGC is a cost-efficient method to induce renewables production and to reduce emissions. Del Río and Miguel (2004) explain why TGC is a cost-efficient method that in theory, TGC ensures that the cheapest renewable technologies will be made with investments, and low-cost deployment of investment will induce these technologies and therefore achieve the quota targets for each country at the lowest possible costs.

Different sources show that six countries in the European Union (EU), where two regional TGC systems in Belgium (De Lovinfosse, 2008) included, have applied the TGC schemes with other schemes to induce the renewables production. Although the structure of the TGC system is adopted by these countries, it is noticeable that differences to some features among these TGC schemes are existing. To begin with, obligated actors are different among countries. Suppliers from Belgium, Sweden and the United Kingdom (UK) are on behalf of the customers, and they are obligated actors under the TGC schemes. In Italy, producers and importers of non-renewable-based electricity would be obligated to a quota of renewable-based electricity every year (Nvalue AG, 2015). In the Netherlands, TGC is on a voluntary basis (Oikonomou & Mundaca, 2008). Consumers on a voluntary basis pay extra for the usage of renewable-based electricity. Producers of renewable-based electricity in the Netherlands are incentivised by technology-specific FIT, and TGC through the reduction in paid regulatory energy tax. Moreover, the circulation of penalties for not complying with the system are different between countries. Retailers in Sweden must pay a penalty for insufficient certificates without recycling whilst buy-out payments required of electricity companies in the UK which obtain insufficient certificates will be recycled to suppliers that have presented sufficient certificates.

The Electricity Certificate Scheme in Norway is an incentive scheme implemented to induce renewable-based electricity production capacity by providing incentives to producers to develop renewables at the lowest possible cost to the society. However, this system has different features than other TGC systems in Europe. In comparison with other TGC systems in Europe, short duration (eight years) and abrupt termination (no phase out period after 2020) have been examined specifically as the features in the Norwegian Electricity Certificate Scheme by Linnerud and Simonsen (2017). They found out that different types of investors have a homogeneous response that they would lock in future subsidies by investing immediately and become pessimistic with the risk barriers as the certificate deadline neared. The report from NVE (2019) shows that renewable-based electricity production so far has reached the Swedish-Norwegian joint market target of 28.4 TWh additional annual production by the end of 2020, but findings from Linnerud and Simonsen do not include whether TGC system will have positive effect to the development of the renewables, which we have interest to investigate. Moreover, by reading Bye and Hoel (2009), another question about whether the Electricity Certificate Scheme acts at the lowest possible cost to the society, or to the polluters to develop renewables arises. They emphasise two features in Norwegian energy market in their study: certificate exemption for the manufacturing and low price in the certification market. They further combine the features with the goals of the Electricity Certificate Scheme and conclude that the Electricity Certificate Scheme is an expensive scheme to reduce emission which was not paid by those who are responsible for the pollution.

The literature provides us with necessary background and pre-implementation analysis regarding the incentive scheme of interest. We would like to empirically assess the post-implementation efficacy of the Electricity Certificate Scheme on the development of renewable energy in Norway in this thesis.

3 The Norwegian – Swedish Electricity Certificate Market (TGC-M)

The Electricity Certificate Scheme is a national-level support scheme that EU Member States use as a basis for inducing renewable production by requiring either energy producers to obligate a given proportion of renewable-based energy in their production portfolio or energy consumers to include a given proportion of renewable-based energy in their consumption.

There are two clauses from EU Renewable Energy Directive 2009/28/EC that form the legal foundation of the bilateral agreement of Norwegian – Swedish Electricity Certificate Market (TGC-M), which is a common market for trading of Electricity Certificates between Norway and Sweden. Firstly, Member States recognize certification awarded by other States in accordance with criteria mechanisms. Secondly, Member States of EU and EEA are allowed to “agree on the extent to which one Member State supports the energy production in another, and to what extent the energy production from renewable sources should count towards the national overall target of one or the other” (European Union, 2009). Hustveit (2015) mentioned that the TGC-M is adapted to the dynamic equilibrium model of Coulon (2015), which accumulated number of certificates, value of the certificate, annualised issuance of certificates and increase in generation can be represented mathematically with given assumptions and adjustments.

Under TGC-M, Norway and Sweden aim to achieve the production goal of electricity from renewable sources (including hydropower, wind power and bioenergy) by 28.4 TWh between 2012 and 2020 (NVE, 2019) in a more efficient and cost-effective way than by having it in the Norway and Sweden market separately. In other words, TGC-M can use renewable resources and financial support more efficiently than separate regional markets because both liquidity will be increased as there are more participants in the joint market than single market, and investment decisions will be made optimally as both Norwegian and Swedish electricity producers can receive financial support from the scheme. Norway and Sweden, the two next-door neighbors, have agreed to share the responsibility of financing increasing green electricity production and the market to decide where and when the new production is to take place. General illustration of TGC-M will be presented in figure 4.1.

It is important to mention that Electricity Certificates are traded at TGC-M, not the power trading market. A short introduction of power trading in Norway is as follows. The liberalisation of the power market started with The Energy Act of 1990, when Norwegian customers were able to purchase power from a supplier of their choice (The Norwegian Government, 2016). The Nordic countries (Norway, Sweden, Denmark and Finland) had free competition in their power market in the early 1990s and brought their individual markets together into a joint Nordic market where electricity production and trading should be market-based (Nord Pool, n.d.).

When taking TGC-M and the power market locally, there are five power bidding zones of power price in Norway, yet the number of bidding zones for Electricity Certificates in Norway is only one. Both power and Electricity Certificates are traded-based in their separate markets and paid by the end users. Although TGC and power are traded at the separate market, we have the interest to know if the power market has connection with the TGC-M. The connection between these markets will be investigated in the methodology section.

Regarding the mechanism of the TGC-M, electricity producers would first receive one Electricity Certificate for each MWh of electricity produced from renewables (biofuels, geothermal, solar, hydro, wind and wave energy) for a maximum of 15 years. Electricity Certificates from both Norway and Sweden are traded by the Entities in Charge of Maintenance (ECM) where the price is determined by supply and demand. Demand for Electricity Certificates is created by electricity producers, and some electricity end users who are obligated by the law to buy Electricity Certificates corresponding to a quota, which means proportion of their electricity sales or usage. Electricity end users pay for the cost of Electricity Certificates and therefore the TGC-M is financed by them. The body with quota obligation is preliminary electricity suppliers and some electricity end users, and they must cancel electricity certificates each year. In this way, a demand for Electricity Certificates is constantly being created, and the quota obligation can be fulfilled (NVE, 2013).

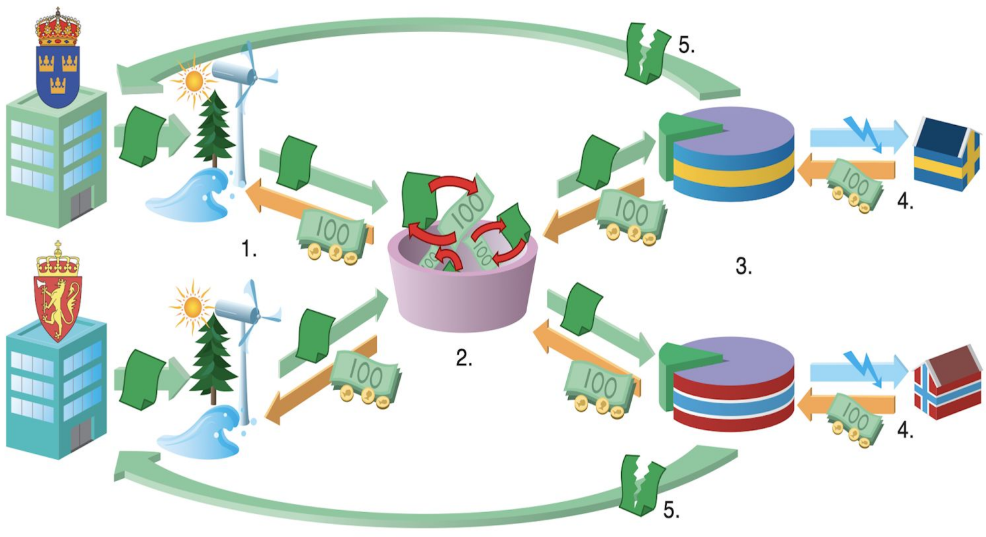

Figure 3.1 Illustration of Norwegian – Swedish Electricity Certificate Market

(Source: NVE)

Even though the fundamental principles in this scheme are the same, some important differences between Norway and Sweden under TGC-M need to be noted. Both assignment periods for approved plants are 15 years from 1st March 2003 in Sweden whilst 1st January 2012 in Norway. Both countries define end users who use their own electricity and have bought electricity from Nordics electricity exchange are with a quota obligation. Still, user-end electricity distributors in Norway whilst electricity suppliers, end users and electricity-intensive industries in Sweden are defined as other market participants with a quota obligation. There is a joint council for one TGC-M with two national regulatory frameworks, different management and accounting agencies and supervisory authorities.

NVE announced that Norway and Sweden have achieved the production goal of green electricity in Norway and Sweden by 28.4 TWh on 24th May, 2019 (NVE, 2019) and overreached when new green electricity production of 23.9 TWh in Sweden and 10.5 TWh in Norway under the Electricity Certificate Scheme, where more than half of these production in Norway are generated from Southern and Middle Norway (NVE, 2020). Spot price on Electricity Certificates in Norway and Sweden had converged to be equivalent from December 2016 and ended with 50 NOK per certificate in December 2019.

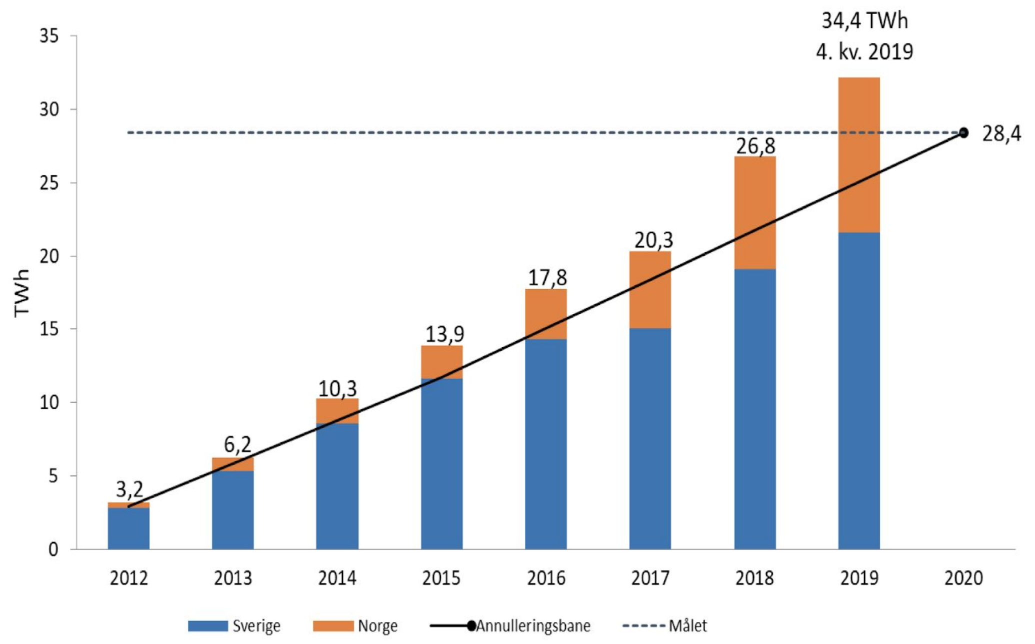

Figure 3.2 Approved TGC construction sites in Norway and Sweden

(Source: NVE)

Figure 3.3 Monthly average spot price for electricity certificates traded via Svensk Kraftmäkling (Source: NVE)

In Sweden, around 30 plants commissioned in the electricity certificate system in 2003 were phased out in 2018 because of the 15-year assignment period. In Norway, assent to the legislation of The Norwegian Electricity Certificate Act ("Lov om elsertifikater") had been given in June 2011 by the Norwegian parliament (Stortinget, 2011) without further amendments. Therefore, the assignment period for approved plants began to expire from 2020. NVE expects that numerous plants with 11,076 GWh expected normal annual production will phase out in 2033 (NVE, 2019). Moreover, this also means that there is no new target for Norway under the Electricity Certificate Scheme after 2020, when Electricity Certificates-qualified renewable plants must be commissioned by corresponding authorities in order to receive said certificates.

4 Data description

In this section, we describe three datasets collected and analyzed in this master thesis. Each of them delivers specific information which requires different empirical approaches.

4.1 Intra-national difference-in-differences analysis: nationally aggregated monthly electricity production data

For the intra-national analysis, we use the nationally aggregated monthly electricity production data of hydro, wind and thermal power plants within Norway in the period from January 2004 to December 2019 retrieved from electricity balance data (table 08583) published by Statistic Norway. These three sources are chosen for our analysis as they are the most commonplace electricity sources in Norway (NVE, 2020). Databases for these three sources are also the most comprehensive public databases we can find.

By definition, electricity produced from biofuel, geothermal energy, solar energy, hydropower, wind power and wave power is eligible for the Electricity Certificate Scheme (NVE, 2015). In the case of Norway, hydropower has been the dominant source of electricity which covers approximately 93% of the nationwide electrical demand (NVE, 2019). Wind power has been rising to be a potential source of electricity in recent years, yet it remains an immature technology which attracts soaring investments. Although thermal power generated from biogas is eligible for the scheme, thermal power plants in Norway are mostly based on natural gas, gas or heat from industrial processes and waste incineration (NVE, 2020), all of which fall out of eligibility for financial support from the Electricity Certificate Scheme. Data of solar- and wave-based electricity are excluded from this thesis due to the limited data accessibility.

Therefore, categorically speaking, only hydro and wind energy are qualified for our analysis regarding the impact of the Electricity Certificate Scheme. Thermal-based electricity production would be used as the control group. Reported production of thermal energy in Norway has always been comparable and more stable than that of wind power (NVE, 2020) and most of such thermal-based electricity is used for regular in-house purposes. Consequently, thermal-based electricity production, being the most feasible option, is entitled to be the control group for our DiD analysis.

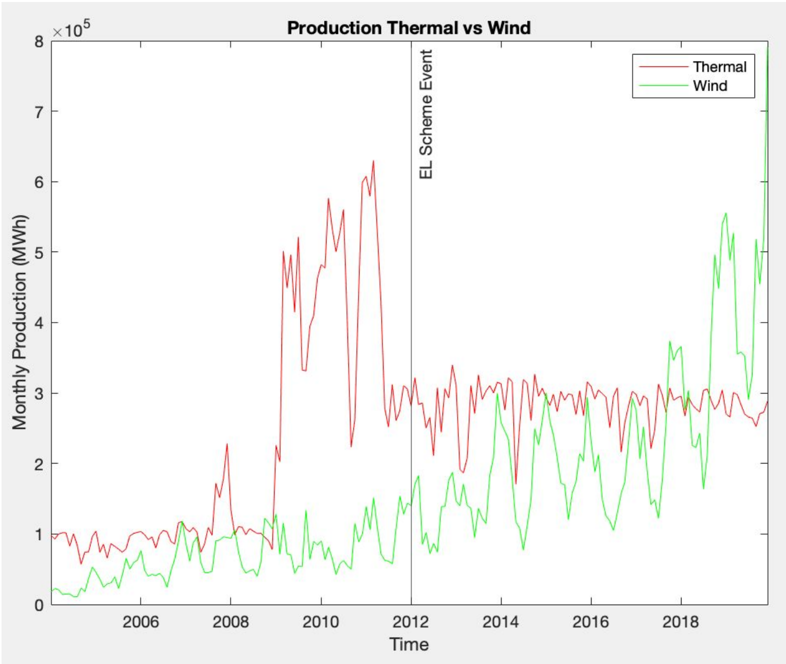

Figure 4.1 Monthly electricity production from Thermal vs Wind power plants in Norway from January 2004 to December 2019

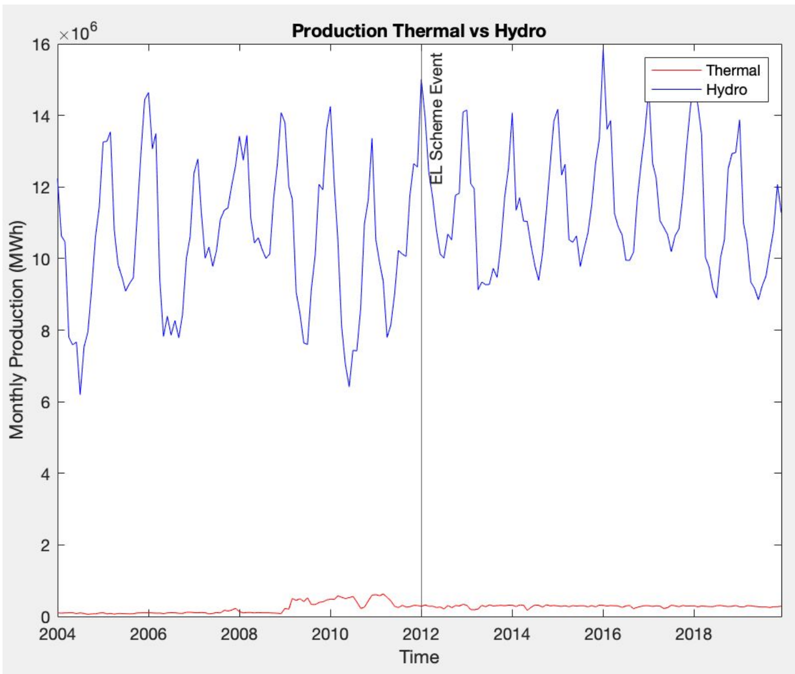

Figure 4.2 Monthly electricity production from Thermal vs Hydro power plants in Norway from January 2004 to December 2019

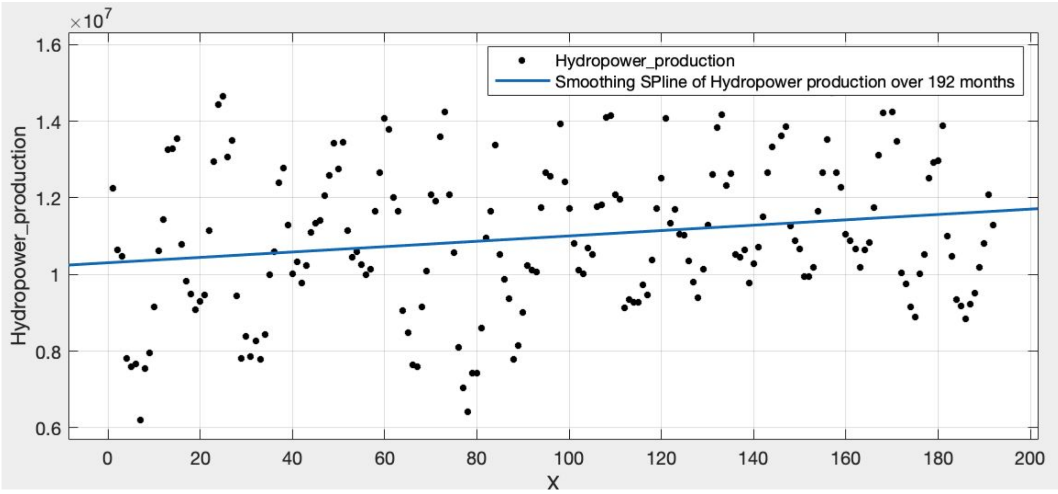

Figure 4.3 Smoothing SPline of Hydroelectricity production

Figure 4.1 and 4.2 show that electricity output from hydro and wind sources has been increasing, though with different magnitude, over time. Although the wild fluctuation in hydroelectricity production may somewhat disguise the increasing trend, the smoothing SPline in figure 4.3 confirms such upward movement. Figures of hydro and wind also present the seasonality as well as provide a rough comparison between electricity output of hydro/wind power plants and that of thermal ones. Regardless of monthly fluctuations, we lay more focus on the general positive development in the electricity production of hydro and wind power plants.

It is unnecessary that parallel lines have to be strictly linear as time-fixed effects allow for flexible time trends that move up or down across from period to period which has been mentioned in Wing, Simon & Bello-Gomez (2018) and Sommers et al. (2015).

4.2 International synthetic control analysis: monthly electricity supply panel data from European countries

4.2.1 Electricity production data

For the international level, data of monthly electricity supply (or net production) from renewable sources of 27 European countries from EuroStat had been deployed in the synthetic control method. The data, measured in GWh, is available from January 2008 to December 2019, which is presumably a sufficient length for pre- and post-treatment periods combined. The original datasets acquired contain production records of electricity from various sources such as hydro, wind and geothermal power. However, only the record of hydroelectricity will be sufficient and thus adopted for data analysis as it contains fewest missing and/or zero data points. After screening and excluding missing data points in the dataset, observations for 26 (25 in certain robustness tests) countries in a period of 140 months from January 2008 to August 2019 are taken into use. Of 26 countries, we have Norway as the main treatment country while the other 25 be the donors for the synthesis of a comparable yet non-treatment "Norway". The donor pool consists of Belgium, Bulgaria, Czechia, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Italy, Latvia, Lithuania, Luxembourg, Hungary, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden and the United Kingdom.

Regarding the initial screening to exclude missing data points, we interpolate as well as extrapolate (also known as forecasting) missing data for a more precise analysis. Interpolation is solely necessary for Croatia and Iceland because data from 2008 to 2011 of Croatia is missing while Iceland holds discontinuous time series. To interpolate the missing data, we have taken several methods such as the "FORECAST" function in Excel, Smoothing SPline, Cubic and Modified Akima Cubic Hermite in Matlab into consideration. "FORECAST" function in Excel, using linear regression (Weisel, 2009), has been chosen to "backcast" those missing data so that we can include one or both countries in our synthetic control models. This is because it is the most easily applicable tool to use on a heavily missing dataset while other methods are either overwhelmingly complicated or return extravagant and thus unanalyzable results. Therefore, we keep our interpolation to the linear forecasting method for the time being.

Extrapolation is applied to most of the countries in our dataset but not to a great extent as there are very few end-of-period missing observations that need to be forecasted. In order to optimise the coding process, the extrapolation method ARMA(2,1) model that takes the autoregressive nature of time series into account has been employed in all countries. The reason is that only 2 to 3, 4 observations at most are forecasted by ARMA so it does not seem to be worth the effort to argue or find the optimal ARMA specification. In addition, the overall result with those forecasts is exactly the same without forecasting.

We are aware that in the literature employing this method, for instance Abadie, Diamond & Hainmueller (2014) and Andersson (2019), the synthetic control often has the similar levels and paths of the variable of interest. However, the donor country production levels (figure 4.4) illustrates that the available datasets in our project do not allow for similar levels of hydroelectricity production. This might be because Norway has more superior natural conditions, development history and strategies for hydroelectricity than other countries in the donor pool. Therefore, the data only allows us to derive a synthetic Norway sharing a resembling development path in hydroelectricity production which complies with the similar paths prerequisite.

Illustration of the production level incompatibility is as follows:

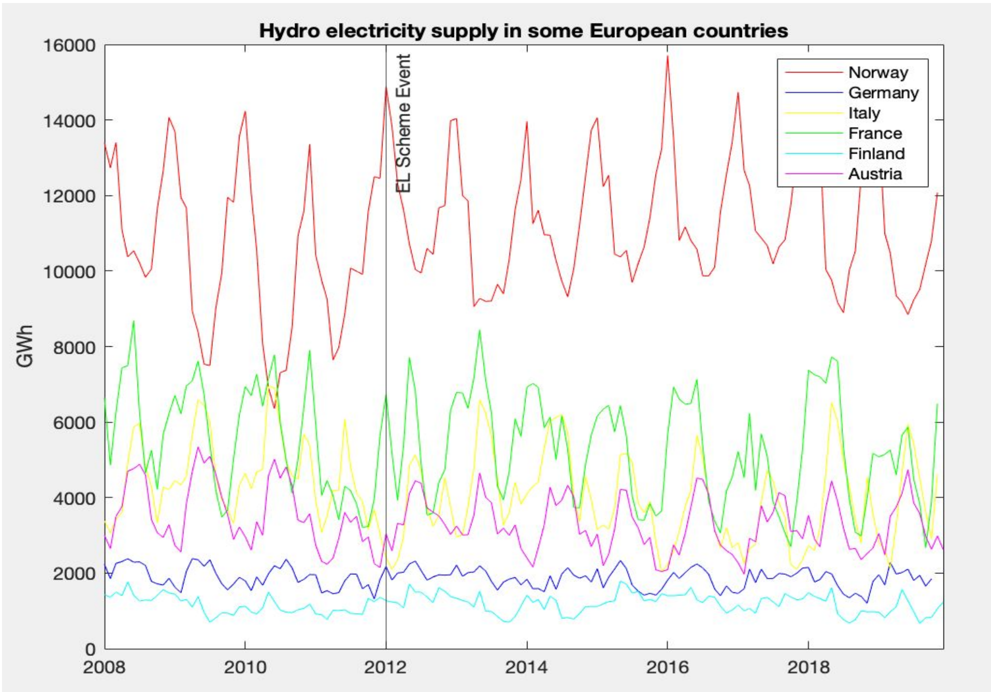

Figure 4.4 Monthly hydroelectricity supply/production in some sample European countries from January 2008 to December 2019

4.2.2 Predictors data

As key predictors, we use electricity consumption, electricity price, environmental tax as a percentage of GDP, and share of renewable energy in total gross energy consumption. As mentioned in the literature, electricity consumption, electricity price and environmental tax are influential on renewable energy production. To be more specific, Romano et al. (2017) empirically proves the positive impact of electricity price as well as consumption on the amount invested in renewable energy development while Zhao et al. (2013) claims that renewable electricity policies including certain types of environmental tax help push renewable energy production. In addition, we would like to incorporate the share of renewable energy in total gross energy consumption to derive the best equivalent synthetic non-treatment Norway from the donor pool with respect to the popularity of renewable energy in the national energy portfolio. We average the four key predictors over the pretreatment period, yet the definite pre-treatment period span depends on the availability of data on each predictor.

4.3 Auxiliary data analysis

4.3.1 Dependent variables: concession data from NVE - applied production and capacity

In our regression models, we use concession data of individual renewable power plants in Norway in the period of 2006 - 2018 as dependent variable with an aim to extract the influence of the electricity certificate scheme on the building authorization, thus development, in new renewable power plants (hydro and wind power plants in our project's scope). To be more specific, concession data include approved capacity and output for a tentative power plant in its registered region, measured in MW and GWh respectively. Such data then are categorized into a monthly and regional basis. We apply ELspot regions featured on Nordpool's website into our analysis due to the differences in electricity prices among those regions.

4.3.2 Independent variables

The independent variables in our regression models are divided into four categories: policy-related (Electricity Certificate Scheme), other policy-related (other environmental policies), market-related and macroeconomics. Among those explanatory variables, electricity certificate scheme variables consist of electricity certificate price (NOK/certificate), electricity certificate quotas (percentage) and electricity certificate annual cancellation. These three variables are the quantitative data featuring the mechanism of our certification scheme and effect on the development of the renewable-based electricity market, which needs to be studied. While the certificate prices are decided on various contract types (intraday, day-ahead and forward contracts) which are possible to aggregate to a monthly frequency, certificate quotas and cancellations are imposed in an annual manner. It is therefore noticeable that such a discrepancy may reduce the significance of our regression models, yet we spent our best effort to incorporate those variables into our analysis.

In the other policy-related category, we choose to use environmental taxes (in million NOK) along with greenhouse gas emission (Tonnes CO2 equivalent per million NOK). Marques, Fuinhas & Pires Manso (2010) and Marques & Fuinhas (2011), studying panel data of European countries, concluded that carbon dioxide emission has an impact on the development of renewable energy. Meanwhile, environmental taxes, among other governmental interventions supporting renewable energy, is proven to be effective in J. Vehmas et al. (1999).

By definition, the electricity certificate scheme involves electricity market participants. Therefore, certain aspects of the electricity market such as electricity price (in day-ahead contracts, averaged to a monthly basis), net consumption of electricity per month in Norway and grid rent tax (øre/kWh) should be taken into account when analyzing the effect of such policy. This line of reasoning is also backed up by Romano et al. (2017) and Mauritzen (2013). In addition, classification of electricity price by the governing body (Nord Pool in this case) steers us to include dummies for regional effect. We use four dichotomous variables to indice NO1, NO2, NO3 and NO4, leaving NO5 the baseline to avoid causing perfect collinearity in our models.

Finally, no policy can work in isolation and an electricity certificate is not an exception. The scheme is introduced into a dynamic macroeconomic environment, hence undergoing extensive influence as well as complicated interactions with other general economic factors of the time being. We are aware that a full coverage of every single macroeconomic aspect is nearly impossible. Therefore, based on the literature, we incorporate a limited number of key factors into our models. First, the income effect on renewable energy development, measured by GDP or GDP per capita, is recurrently tested (for example Narayan and Smyth, 2008; Chang et al., 2009; Sadorsky, 2009b). In a similar way, we use absolute economic size measure (GDP) and not the standard of living of a population as the explanatory variable. Second, improving renewable energy infrastructure and production appear to politically motivate the employment market, creating jobs and boosting economic growth as mentioned in Ydersbond & Korsnes (2016). This leads us to take monthly unemployment rates into account in the macroeconomic category.

5 Methodology

In this section, we summarize the empirical methods adopted in our analysis. Our focus is lay on DiD and its derivative - the synthetic control method. There are four main reasons to choose these two specific methods. First, as mentioned in previous sections, the Electricity Certificate Scheme, which was implemented in Norway in 2012, has the fundamental characteristic of an "event" with pre- and post-treatment timespans, prompting us to utilize quantitative methods for event study. Second, the availability of datasets on various forms of renewable electricity production orients us to work on empirical comparison. Third, previous literature, especially ones concerning environmental and/or other policies such as Ydersbond & Korsnes (2016), Abadie et al. (2015) and Andersson (2019), have successfully employed DiD, synthetic control method and other quantitative comparison models to derive the effectiveness and efficiency of those policies. Last but not least, the two methods used in our thesis are well-founded and easy to replicate with detailed instructions and discussions in related articles (Meyer, 1994; Donald & Lang, 2007; Abadie et al., 2015 and Fredriksson & Oliveira, 2019). On such grounds, we are confident that the two quantitative methods would appropriately and efficiently reach desired results.

5.1 Difference-in-differences analysis

According to Angrist & Pischke (2008), DiD analysis is a statistical technique used in econometrics and quantitative research in the social sciences that attempts to mimic an experimental research design using observational study data, by studying the differential effect of a treatment on a "treatment group" versus a "control group" in a natural experiment. This method is best employed when one wants to extract the real effect of a specific treatment (or Electricity Certificate Scheme implementation in our project) among many other influential forces beside the treatment itself. To be more precise, the actual effect of the Electricity Certificate Scheme on the renewable-based electricity production from renewable energy power plants is calculated by comparing the average change over time in the outcome variable for the treatment group (which includes hydro and wind-based power plants in Norway) to the average change over time for the control group (thermal power plants in Norway).

As mentioned in Fredriksson & Oliveira (2019), inclusion of a control group along with the original treatment group helps us achieve two things. First, changes over time caused by non-treatment forces are captured and netted out from the impact estimate. Second, if there are important factors that are determinants of outcomes and that remain consistently and constantly different between the treatment and control groups, then their influence is eliminated by studying changes over time. Importantly, this latter point applies also to treatment-control group differences in time-invariant unobservable characteristics (as they are netted out). It is thus possible to fix the problem, present in cross-sectional studies, that one cannot control for unobservable factors.

5.2.1 Assumptions

Estimation of DiD models hinges upon several assumptions, which are discussed in detail by Lechner (2011). We would like to briefly summarize those assumptions while concentrating on the most important assumption of "parallel trends", which is an emphasized requirement for any paper using DiD analysis.

The first assumption is stated as that one, and only one, of the potential outcomes is indeed observable for every member of the population, following from the so-called Stable Unit Treatment Value assumption in Rubin (1977). It implies that the treatments are completely depicted and particularly that there are no relevant interactions or mutual effects between the members of the population. This assumption clearly defines the "treatment" and draws the line between treatment and control groups.

The second assumption, noted as "too strong" by Lechner (2008a), is called exogeneity. To be more specific, the control variables at disaggregate levels should be unaffected by the treatment, i.e. exogenous. This assumption is not necessary in our model as we do not take those control variables into account, and hence only stated here for a complete assumption set.

While the two assumptions above are fundamental in causal studies, the next one is specific to DiD. Here the pre-treatment period the treatment must have no effect on the pre-treatment population to rule out any possibility of behavioral changes in anticipation of upcoming treatment.

The last two, yet also the defining assumptions of DiD, are "common trend" (or later mentioned as "parallel trend") and "bias stability" assumptions.

DiD requires parallel trend assumption, which means evidence for comparability over time of the two groups in absence of the treatment (Meyer, 1995). This assumption states that the differences in the expected potential nontreatment outcomes over time are unrelated to the group membership post-treatment period. In other words, it implies that without the presence of the treatment, both subpopulations would have experienced the same time trends.

One complication one might encounter is that such an assumption is basically untestable because there are only "treated" observations of the treatment group. Fredriksson & Oliveira (2019) outlined certain ways to back up the assumption, among those are pattern detection from several pre-treatment periods, placebo regression and addition and disprovement of specific time trend terms for the treatment and control groups. Unfortunately, those solutions are inapplicable to a dataset with only one pre-trend period like ours. We therefore acknowledge that our analysis is less robust than optimum and follow the reasoning line in Data

Description to assume a loose equivalence in development trends of hydro, wind and thermal electricity production so that the parallel trend assumption is fulfilled.

Bias stability assumption draws on the intuition of a correctable constant bias upon observation selection between treatment and control group. This final assumption reinforces the underlying "scale-dependent" characteristic of the parallel trend assumption, claiming that we are indeed comparing trends at specific values and not comparing absolute values or monotone transformation of values.

5.2.2 Implementation

The general underlying model, adapted from Meyer (1994), is as follows:

$$y_t = \beta_0 + \beta_1.T_t + \beta_2.S_t + \beta_3.(T_t.S_t) + \varepsilon_t$$

In which:

t is the time index, counting on a monthly basis from 1 as of January 2004 to 192 as of December 2019.

β_0 is the constant term which is generally included in a regression model to represent the intercept of the linear regression line with the y-axis.

T is the dummy variable for time which equals 1 when $t \geq 97$ (after the point of the year 2012 when Electricity Certificate Scheme was carried out) and 0 otherwise. Here we define pre- and post-treatment span to be: January 2004 - December 2011 and January 2012 - December 2019 regarding one-time change in policy in 2012 when Norway joined Sweden to form a common tradable electricity certificate market. The parameter β_1, intuitively, captures how both groups are affected over time by any non-treatment forces.

S is the dummy variable for group membership which equals 1 if the observation belongs to the treatment group, or in our case, hydro or wind energy production, and 0 otherwise. Consequently, the coefficient β_2 captures any time-invariant difference between the overall means of the two groups.

The composite dummy $(T.S)$ presents observations in the treatment group after receiving the treatment, and hence β_3 is the true effect of the treatment on the outcome of this group. We therefore lay our interest in the value and significance of the parameter β_3.

ε is the error term of the model which is defined as the difference between the expected production and the actual production at a specific time point t. One crucial condition for the estimated parameters to be BLUE is that $E[\varepsilon_t] = 0$.

5.2.3 Model diagnostics

The purpose of performing model diagnostics is to see whether the models fulfill the prerequisite Ordinary Least Squared (OLS) regression assumptions and thus whether the models are statistically significant and valid. We also consider this procedure as an opportunity to investigate possible underlying errors and revise the models where necessary.

We plot Cook's distance among residuals, plot distribution histogram and scatter residuals of each model in order to detect heavily influential outliers, abnormality in residuals' distribution and heteroscedasticity as well as autocorrelation in the error terms. While heteroscedasticity does not necessarily invalidate the unbiasedness of the Ordinary Least Squared (OLS) regression, it violates the assumption of homogenous variance in modelling errors and thus triggers inefficiency in the estimation of the parameters' variance. Autocorrelation in the error terms, on the other hand, directly violates the OLS assumption that the error terms are uncorrelated, and thus invalidates OLS estimators as the Best Linear Unbiased Estimators (BLUE).

If one and/or another model criterion is not fulfilled, we adjust the models in several manners. Those fixing manners consist of removing heavily biased outliers whose residuals exceeding this threshold value of three times of the average of the residuals' Cook's Distance and using Newey - West or heteroskedasticity and autocorrelation consistent covariance (HAC) estimators which return robust covariance estimates for OLS coefficient estimates of multiple linear regression models under general forms of heteroscedasticity and autocorrelation in the innovations process. The HAC process does not necessarily change the estimation of model parameters but rather addresses the incorrect standard errors and makes them robust.

5.2.4 Strengths and weaknesses

The DiD method is confirmed to have a statistically better performance than the traditional differences regression analysis. The conventional pretest - posttest regression models are based on the idea of deriving any possible effect of a certain event on the treated group of outcome variables using one dichotomous variable for timing. However, this method is highly unlikely to lead to valid inferences (Meyer, 1995) due to myriad threats to both internal and external validity. DiD fixes part of those threats by introducing a control group that does not receive the treatment but experiences some or all of other influences affecting the treated one. In that way, some of the threats are lifted off researchers' shoulders, adding credibility to the results.

Despite its superiority, DiD still has some drawbacks. Assumption testing remains the biggest concerns of DiD adopters when the most important assumption - parallel trend - is frustratingly untestable. This gives rise to the problem of omitted interaction, i.e. possibility of an interaction other than the treatment in the treatment group after the event. The unavailability of a strictly comparable control group further builds up on this issue, lowering the trustability of our models. A potential remedy in this case may be to impose the common trend assumption in some latent models, yet it would be too complicated regarding the scope and academic level of our thesis. Therefore, we accept the specified shortcomings in our methodology and leave them for subsequent research.

5.3 Synthetic control method

For the international level, we use synthetic control method to compare the development of renewable energy production in Norway with that of other European countries. The core idea of synthetic control method is to construct a synthetic Norway from the donor pool based on certain key predictors of hydroelectricity production so that it resembles the real Norway on those predictors prior to the electricity certificate scheme and has similar production paths.

5.3.1 Relaxing parallel trend assumption

The parallel trend assumption for the DiD method applied above is indeed difficult to verify, sometimes even untestable and thus require various methods and tools to ensure (Andersson, 2019 and Wing, Simon & Bello-Gomez, 2018). In order to avoid vague assumptions of such trend and undesirable ignorance of possible biased DiD estimators, we preferably opt for a method that relaxes the parallel trend assumption. The synthetic control method stands out to be an effective tool for our comparative analysis. The main advantage of this method is that it allows the effects of unobserved confounders on the outcome variables to vary overtime by weighting the control group so that prior to treatment it resembles Norway on a number of key predictors of renewable energy production and has similar paths of renewable-based electricity production. In short, the method relaxes the assumption of specific, country-particular parallel trends in conventional DiD regression, thus improving the real-effect estimator (Abadie, Diamond & Hainmueller, 2015). So far in the literature this is one rare method that succeeds in relaxing the parallel trend assumption.

5.3.2 Weight vector and optimization problem

Synthetic Norway is constructed as a weighted average of the donor countries and presented by weight vector W in which each component, correspondingly weight for each donor country, is restricted to lie between 0 and 1 with the total sum of weights equal to 1. Choosing a particular W, or a certain set of weights, is therefore equivalent to choosing a unique version of synthetic Norway.

W is selected on the ground of minimized differences between synthetic and real Norway on a number of key predictors on the outcome variable and the outcome variable itself. The employed set of predictors is mentioned and explained in Data Description. This set of predictors are also assigned weights to align with individual relative importance. There are various methods available to constructing predictors' weight vector V, yet we follow Abadie, Diamond, and Hainmueller (2010) to exercise optimization by minimizing the Mean Squared

Prediction Error (MSPE) of the outcome variable over the entire pre-treatment period. We thank them for the publicly shared Matlab codes used to run our models.

5.3.3 Model specification

Let $I+1$ be the number of European countries in our data set. The index i represents the countries with $i=1$ denoting Norway as the treated agent while $i=2,3,...,I+1$ denoting the donor countries. Time periods are, as usual, denoted as $t=1,2,...,\ T$ with the specific point of $T_0,\ 1<T_0<T$, signalling the time of treatment (the year 2012 when the Electricity Certificate Scheme was implemented). Now let p_{it} be the hydroelectricity production of country i at time t.

The synthetic Norway is constructed as follows:

$$NORsynth_t = W \times P_t$$

In which:

$W=(w_2,\ w_3,...,w_I)'$ is the donor weight vector on condition that $0 \leq w_j \leq 1$ and $\sum_{j=2}^{I} w_j = 1$.

$P_t=(p_{2t},\ p_{3t},...,\ p_{It})$ is the hydroelectricity production vector of the donor pool at time t.

Afterwards, the difference-in-differences regression analysis is specified:

$$y_t = \alpha_0 + \alpha_1.T_t + \alpha_2.S_t + \alpha_3.(T_t.S_t) + \varepsilon_t$$

In which:

y is the hydroelectricity production of either Norway or synthetic Norway.

t is the time index, counting on a monthly basis from 1 as of January 2008 to 140 as of August 2019.

α_0 is the constant term which is generally included in a regression model to represent the intercept of the linear regression line with the y-axis.

T is the dummy variable for time which equals 1 when $t \geq 71$ (after the point of the year 2012 when Electricity Certificate Scheme was carried out) and 0 otherwise. Here we define pre- and post-treatment span to be: January 2004 - December 2011 and January 2012 - August 2019 regarding one-time change in policy in 2012 when Norway joined Sweden to form a common tradable electricity certificate market. The parameter α_1, intuitively, captures how both groups are affected over time by any non-treatment forces.

S is the dummy variable for group membership which equals 1 if the observation belongs to the treatment group, or in our case, Norwegian hydroelectricity production, and 0 for that of the synthetic Norway. Consequently, the coefficient α_2 captures any time-invariant difference between the overall means of the two groups.

The composite dummy $(T.S)$ presents observations in the treatment group (the real Norway in this case) after receiving the treatment, and hence α_3 is the true effect of the treatment on the outcome of this group. We therefore lay our interest in the value and significance of the parameter α_3.

ε is the error term of the model which is defined as the difference between the expected production and the actual production at a specific time point t. One crucial condition for the estimated parameters to be BLUE is that $E[\varepsilon_t] = 0$.

5.3.4 Model diagnostics

Model diagnostics are performed similarly to those of DiD because the synthetic control method is indeed an extended and slightly modified DiD analysis.

5.3.5 Robustness tests

In order to further strengthen our results by probing the main assumption underlying the research design, we run several deviations of the main synthetic control model to test for robustness and sensitivity. That includes swapping Norway to Sweden to be the treatment country on the ground that both of them are under one common Electricity Certificate Scheme. Furthermore, we group Norway and Sweden as a general treatment region and perform similar synthetic analysis.

The synthetic control analysis is replicated on the interpolated as well as extrapolated dataset as mentioned in section 4. Analysis extension on a more profound database is expected to deliver more trustable and significant results and hence solidify our empirical findings.

5.3.6 Strengths and weaknesses

Synthetic control method is one step towards model reinforcement on ground of DiD analysis. If comparison units are not sufficiently similar to the treated units, then any difference in outcomes between these two sets of units may merely reflect disparities in their nature. The synthetic control method fixes this intrinsic problem by providing a systematic, explicit and definite mechanism to choose comparison units in comparative case studies.

Like all other empirical methods, synthetic control has its own limitations and hence requires proper adjustments (Abadie, Diamond, and Hainmueller, 2015). First, it is of utmost importance to exclude donors affected by the intervention of interest, or Sweden in our case as the country stays under the same Electricity Certificate Scheme as Norway.

In addition, to avoid interpolation biases, the donor pool should be restricted to countries with characteristics similar to the treated one. However, such an attempt would require a more intensive study over numerous qualitative and quantitative aspects of each country and thus be unnecessarily exhausting.

Another reason to restrict the size of the donor pool and consider only units similar to the treated unit is to avoid overfitting. Overfitting arises when the characteristics of the treatment group are artificially matched by combining idiosyncratic variations in a large sample of unaffected individuals. The risk of overfitting can be mitigated by the cross-validation technique incorporated in our modified codes for the models.

Lastly, the applicability of the method requires a significant number of pre - intervention periods as performed in Andersson (2019). The performance of the synthetic control method in tracking the characteristics and realization of the treatment group over an extended period of time prior to the treatment lends credit to its subsequent results. This issue remains the most difficult problem when it comes to our undesirably poor datasets. Therefore, we look forward to upcoming study with access to a more thorough and complete database to strengthen our first-hand models.

6 Results and Analysis

In this section we summarize our findings regarding both intra-national and international analysis of electricity production from renewable energy sources. We have run numerous models for both analysis orientations, and based on models' specification and statistical significance we come to the conclusion of two main models for each of these two analyses. Details of all models' names and description are presented in Appendix 2, table 1 while the main models are discussed thoroughly below. Section 6.1 is to discuss the two DiD models in which we compare the monthly electricity production of Hydro and Wind power plants with that of Thermal ones in Norway. Section 6.2 presents the two focal synthetic control models of Norway versus the synthetic Norway fabricated from a donor pool of 24 European countries.

While the theoretical applicability of the two quantitative methods has been discussed in section 5, their economic interpretation is well explained in the upcoming sections. The two methods simultaneously compliment each other in the sense that the intra-national analysis verifies the positive impact of the Electricity Certificate Scheme on a vertical scale, i.e. a comparison in electricity producing performance between renewable and non-renewable power plants, while the international counterpart replicates the positive outcome on a horizontal scale by comparing the hydroelectricity output of different nations. Combination of the two techniques provides us with a broader, thus more complete, evaluation of the Electricity Certificate Scheme.

6.1 Intra-national analysis

Our main model from this empirical method is model 2 - Hydro vs Thermal (adjusted) and model 4 - Wind vs Thermal (adjusted).

6.1.1 Hydro versus Thermal

In section 5 we have specified our DiD regression model with a set of dichotomous variables indicating pre- and post-treatment periods as well as group membership. The model is then run on a dataset of 384 observations over 192 months, half of which is hydroelectricity production while the other half is thermal power plants' output.

The initial result is model 1 as below:

Table 6.1 Difference-in-differences regression result of model 1 - Hydro vs Thermal

```
Linear regression model:
    production ~ 1 + H + Time + HTreat

Estimated Coefficients:
                    Estimate        SE         tStat       pValue
                   __________    __________    ______    ___________

    (Intercept)    2.2003e+05    1.3671e+05    1.6095        0.10834
    H              1.0285e+07    1.9334e+05    53.199    3.6135e-178
    Time                63917    1.9334e+05    0.3306        0.74113
    HTreat         8.8773e+05    2.7342e+05    3.2467       0.001271


Number of observations: 384, Error degrees of freedom: 380
Root Mean Squared Error: 1.34e+06
R-squared: 0.942,  Adjusted R-Squared: 0.942
F-statistic vs. constant model: 2.06e+03, p-value = 1.2e-234
```

It is clear that the parameter of interest - β_3 or *HTreat* in the result table is statistically and positively significant at 99% confidence interval. The group parameter (β_2 or H in the table) is also statistically significant, confirming the considerable time-invariant difference between the overall means of the two groups. Meanwhile, estimation of the time parameter does not have a noteworthy interpretation. Looking at the result model as a whole, both R^2 and adjusted R^2 are unexpectedly high, leaving us confidence in the fitness of our model.

Diagnostics for model 1 are performed accordingly to Methodology and then presented as below:

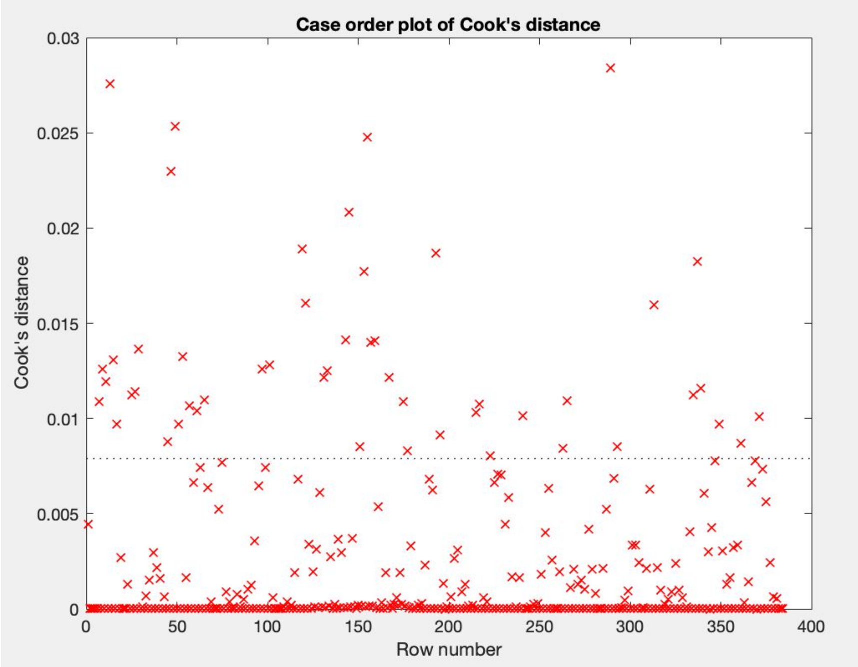

Figure 6.1 Case order plot of Cook's distance for model 1 - Hydro vs Thermal

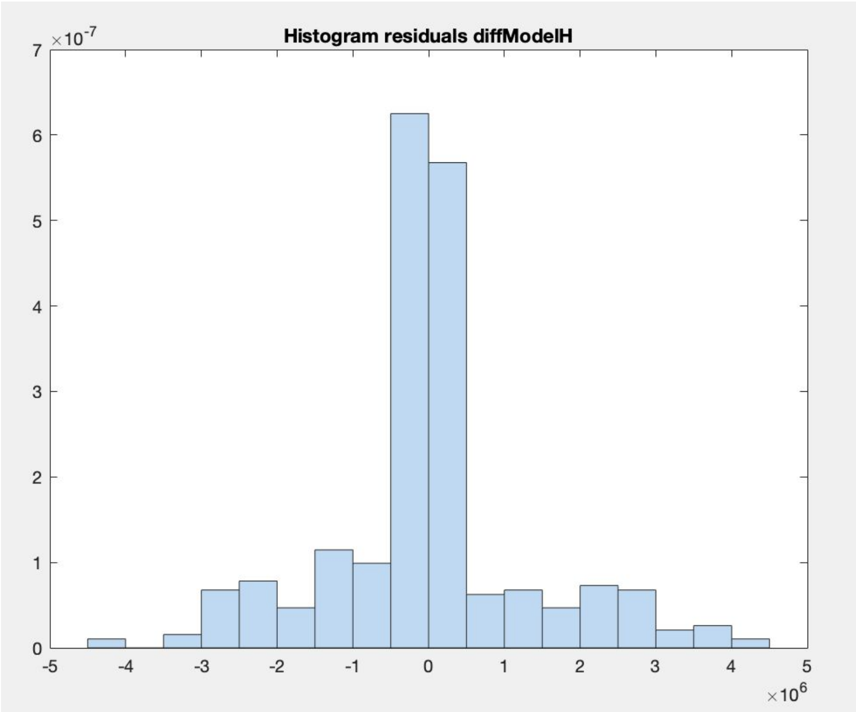

Figure 6.2 Raw residuals histogram of model 1 - Hydro vs Thermal

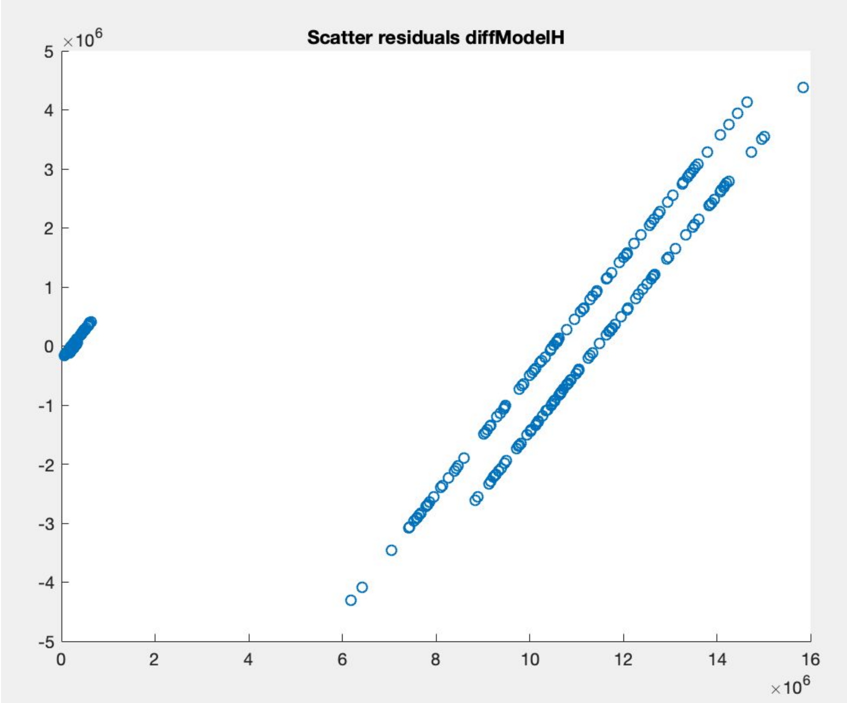

Figure 6.3 Raw residuals scatterplot of model 1 - Hydro vs Thermal

As can be seen in the Cook's distance residual plot, there exist a number of outliers which can be omitted to improve the model's outcome. We proceed with omitting those outliers and refit model 1 to come up with our final model of Hydro vs Thermal - model 2. In addition, the histogram of model 1's residual shows a seemingly normal distribution with most of the residual values being around 0. Meanwhile, the pattern detected among the residuals in the scatter plot signals heteroskedasticity which requires us to use HAC estimators for a more robust result. Fortunately, the HAC coefficients only bear slight differences to the non-adjusted values, thus we confidently conclude on the results of model 2 that there is a positive impact of the Electricity Certificate Scheme on the Norwegian domestic production of hydroelectricity.

Result of model 2 after adjusting for model defects are as below:

Table 6.2 Difference-in-differences regression result of model 2 - Hydro vs Thermal (adjusted)

```
Linear regression model:
    production ~ 1 + H + Time + HTreat

Estimated Coefficients:
                   Estimate         SE         tStat       pValue
                  __________    __________    _______    ___________

    (Intercept)   2.2003e+05         82012     2.6829      0.0076657
    H             1.0385e+07    1.3029e+05     79.708    1.2122e-217
    Time               63917    1.1598e+05    0.55109        0.58194
    HTreat        3.6892e+05    1.7853e+05     2.0664       0.039572


Number of observations: 334, Error degrees of freedom: 330
Root Mean Squared Error: 8.04e+05
R-squared: 0.977,  Adjusted R-Squared: 0.977
F-statistic vs. constant model: 4.73e+03, p-value = 8.8e-271
```

Overall, the intra-national difference-in-differences models provide statistically significant results for model 1 and 2 - Hydro vs Thermal electricity production. It means the electricity certificate scheme appears to have a positive net impact on the production of hydro electricity in Norway. The value of β_3 in model 2 can be interpreted as the real effect of the Electricity Certificate Scheme on hydroelectricity production, or in other words, the certification scheme, after extracting the time-invariant difference between the two energy production forms, seemingly helps boost the monthly hydroelectricity production by 3.69×10^5 MWh more than the output of thermal power plants. The impact is statistically significant at 95% confidence level and the whole model fits to a great extent of 97.7%.

6.1.2 Wind versus Thermal

Similarly to the case of Hydro vs Thermal, the regression model is run on a dataset of 384 observations over 192 months, half of which is now wind power production while the other half is thermal power plants' output. Below is the initial result, or model 3:

Table 6.3 Difference-in-differences regression result of model 3 - Wind vs Thermal

```
Linear regression model:
    production ~ 1 + W + Time + WTreat

Estimated Coefficients:
                    Estimate       SE       tStat       pValue
                   ___________    _____    _______    __________

    (Intercept)     2.2003e+05    11372     19.349    1.5039e-58
    W              -1.5336e+05    16082    -9.5361    1.8206e-19
    Time                 63917    16082     3.9745    8.4403e-05
    WTreat           1.044e+05    22743     4.5904    6.0214e-06


Number of observations: 384, Error degrees of freedom: 380
Root Mean Squared Error: 1.11e+05
R-squared: 0.35,  Adjusted R-Squared: 0.345
F-statistic vs. constant model: 68.2, p-value = 2.76e-35
```

Although all variables of interest, especially β_3 or *WTreat* in the table, are statistically significant at 99% confidence interval, the overall fit of the model is somewhat low (only 35%). We again try to fix this issue by performing residual diagnostics in order to identify and remove outliers while applying the HAC process to the estimators. The outcome is model 4 whose statistical interpretation is the central point of this subsection:

Table 6.4 Difference-in-differences regression result of model 4 - Wind vs Thermal (adjusted)

```
Linear regression model:
    production ~ 1 + W + Time + WTreat

Estimated Coefficients:
                    Estimate       SE        tStat        pValue
                   __________    ______    ________    __________

    (Intercept)    1.4214e+05    7125.7      19.948    1.1317e-59
    W                  -75465      9538     -7.9121    3.3605e-14
    Time           1.4181e+05      9538      14.868    4.2396e-39
    WTreat            -8233.9     13268    -0.62058       0.53528


Number of observations: 354, Error degrees of freedom: 350
Root Mean Squared Error: 6.21e+04
R-squared: 0.64,  Adjusted R-Squared: 0.637
F-statistic vs. constant model: 208, p-value = 2.51e-77
```

Overall, model 3 and 4 present statistical inconsistency and mixed effects of the electricity certificate scheme on wind electricity production in Norway. Model 3 shows positive real effect with a relatively low model power ($R^2 = 0.35$) while model 4, which is achieved by means of proper diagnostics and adjustments to model 3, is inconclusive regarding the parameter of interest. The general fitness of the Wind vs Thermal model is indeed increased by those fixing manners (R^2 increases to 64%), yet it comes at the cost of a statistically insignificant estimation of β_3. Therefore, it is reasonable for us to draw a conclusion only regarding the positive impact of the electricity certificate scheme on hydroelectricity production.

There are two reasons for the inconsistency results among wind vs. thermal models. Such inconsistency may be explained by the weak candidacy of thermal energy as a control group for wind energy. This can be seen in the initial production plot as well as the development history of the two energy sources. As mentioned before, viewpoint from Haas literature supports us in this aspect, saying that tradable certificate systems work more efficiently with mature renewable resources (hydroelectricity in our case). Considering this line of reasoning, we see that wind power, at the time of the Electricity Certificate Scheme introduction, was relatively novice and still struggled in its developing phase (Moe, 2012), thus the electricity certificate scheme may not have a desirable impact on wind-based electricity production.

6.2 International analysis

In this subsection, we follow the model specification in section 5 to perform the Mean Squared Prediction Error (MSPE) minimization of the outcome variable over the entire pre-treatment period over a set of four predictors and arrive at the optimal weight vector W. The weight vector is then multiplied with the donors' monthly production matrix to achieve synthetic Norway, which is in turn merged with the real Norway into a dataset suitable for DiD regression analysis. We run such regression to validify the impact of the Electricity Certificate Scheme on hydroelectricity production of the real Norway.

Initially, we performed our analysis on the donor pool of 25 European countries including Sweden. The preliminary result (available in Appendix 2) shows statistically significant influence of the Electricity Certificate Scheme on the monthly hydro electricity production of Norway with a high model explaining power. However, the donor weight vector of that model seems to be extreme with 100% weight falling on the UK. This biased result prompts us to exclude Sweden in the donor country list because Sweden is also under the common production-incentive scheme with Norway, though with different domestic regulations. Such reasoning leads us to our main synthetic control models (6 and 6.1) which provide far better significant results and model power.

Figure 6.4 shows the path plots of monthly hydroelectricity production of Norway versus synthetic Norway with the chosen weight vector W while figure 6.5 plots the difference between the two Norways throughout the studied time. In section 4 we have pointed out the incompatibility in absolute values between Norway and the other countries in the donor pool. The two plots once again confirm these shortcomings and hence encourage us to focus on pattern compatibility only.

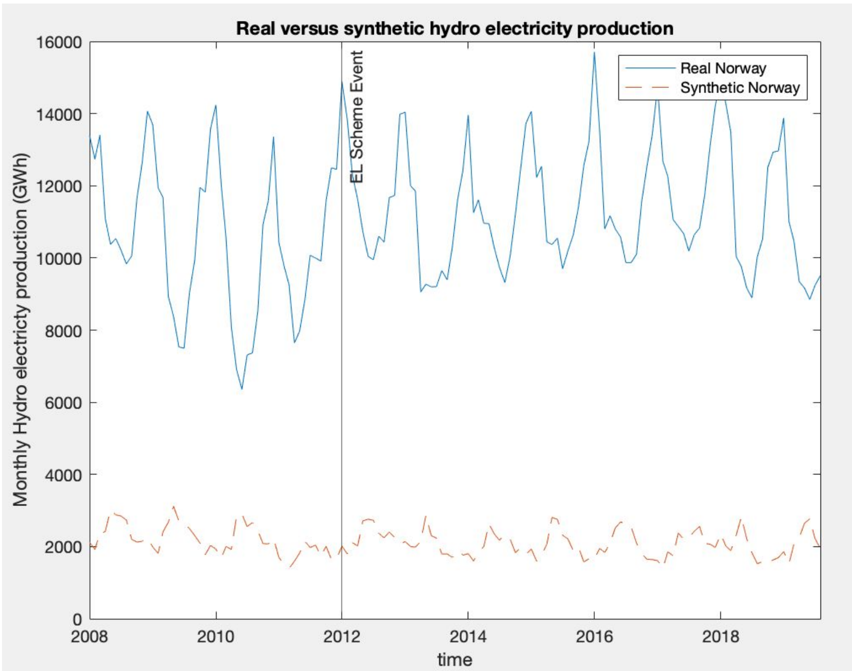

Figure 6.4 Path plots of real vs synthetic Norway's monthly hydroelectricity production

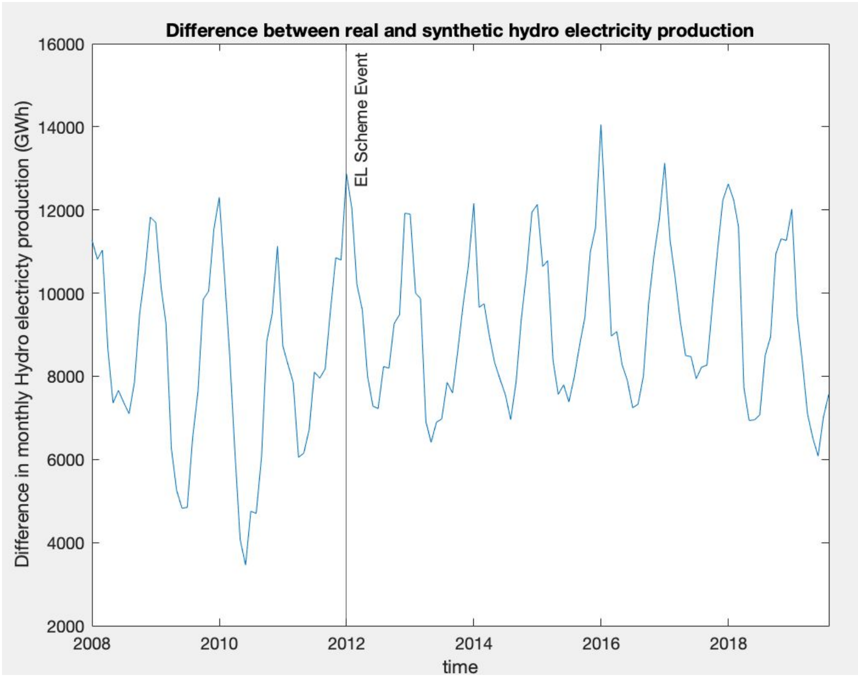

Figure 6.5 Differences between real and synthetic Norway's monthly hydroelectricity production

Table 6.5 Hydroelectricity production Predictors weight means for Norway, synthetic Norway and 28-donor average sample before the implementation of the Electricity Certificate Scheme in 2012

Predictors	Norway	Synthetic Norway	28-donor sample
Average of monthly electricity consumption (GWh)	10755	6625.22	9570.57
Average of annual electricity price (household) (EUR per kWh)	0.17572	0.17569	0.16802
Average of annual environmental tax in GDP (%)	2.67842	2.67813	2.56591
Average of share of RES in gross final energy consumption (%)	67.14927	34.12226	22.57854

Table 6.5 compares the predictors values of the four key predictors in the pre-treatment period for Norway, synthetic Norway and the whole population - weighted donor pool of 28 European countries. It can be easily seen that Norway and its synthetic version have almost identical average values in annual electricity

price and annual environmental tax as a percentage of national GDP and those values are much better fitted than those derived from the whole donor pool. Meanwhile, both synthetic Norway and the average donor sample fit poorly regarding the other two predictors, which can be explained by the historically unique energy portfolio of Norway.

Most importantly, the associating country weight vector for model 6 (see table 6.6) is reasonably distributed in which most of the weight is shared by Finland, Austria and Denmark while the remaining donors receive weights of zero or close to zero. Those dominant countries either share a similar economic and cultural background with Norway or have the same natural and geographical potential in the production of hydro electricity, making the result reasonable and thus trustable.

Table 6.6 Country weights in synthetic Norway - model 6

Country	**Weight**	**Country**	**Weight**
Belgium	0.0000	Lithuania	0.0000
Bulgaria	0.0000	Luxembourg	0.0000
Czechia	0.0000	Hungary	0.0000
Denmark	**0.0373**	Netherlands	0.0000
Germany	0.0000	**Austria**	**0.4465**
Estonia	0.0000	Poland	0.0000
Ireland	0.0000	Portugal	0.0000
Greece	0.0000	Romania	0.0000
Spain	0.0000	Slovenia	0.0000
France	0.0000	Slovakia	0.0000
Italy	0.0000	**Finland**	**0.5161**
Latvia	0.0000	UK	0.0000

The regression result for synthetic control model on the 24-donor dataset over 140 months (model 6) is as follows:

Table 6.7 Difference-in-differences regression result of model 6 - Norway vs synthetic Norway constructed from 24 donors excluding Sweden

```
Linear regression model:
    production ~ 1 + group + time + NORtreatment

Estimated Coefficients:
                    Estimate      SE       tStat        pValue
                    ________    ______    ________    __________

    (Intercept)      2200.6     192.23      11.447    4.3613e-25
    group            8291.4     271.86      30.499    2.2285e-90
    time            -118.78     237.14    -0.50089       0.61684
    NORtreatment       1009     335.36      3.0088     0.0028648


Number of observations: 280, Error degrees of freedom: 276
Root Mean Squared Error: 1.33e+03
R-squared: 0.92,  Adjusted R-Squared: 0.919
F-statistic vs. constant model: 1.06e+03, p-value = 4.48e-151
```

The result above shows that the true effect of the certification scheme, presented as α_3 in the theoretical model and *NORtreatment* in the table above, is positive and statistically significant at 99% confidence interval. The consistent difference between Norway and its synthetic counterpart is also verified by the estimation of α_2 (or the *group* parameter) while time seems to have little impact on both groups. The explaining power of model 6 is noticeably high (92%), signalling a meaningful and trustable model.

Model diagnostics are performed step-by-step as stated in section 5. The case order plot of Cook’s distance (see figure 6.6) highlights a small number of outliers which are afterwards removed for a statistically better model. Figure 6.7 presents the appearingly normal distribution of model 6’s raw residuals while the scatterplot (see figure 6.8) signals concerns about heteroskedasticity. In order to fix that issue, we implemented the HAC estimating command which returns almost identical coefficients with the original model.

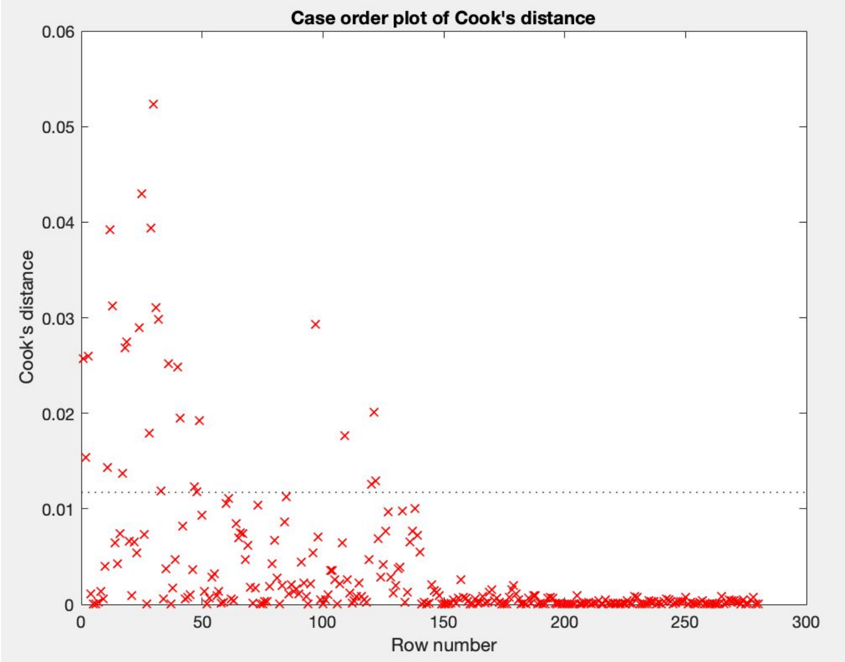

Figure 6.6 Case order plot of Cook's distance for model 6

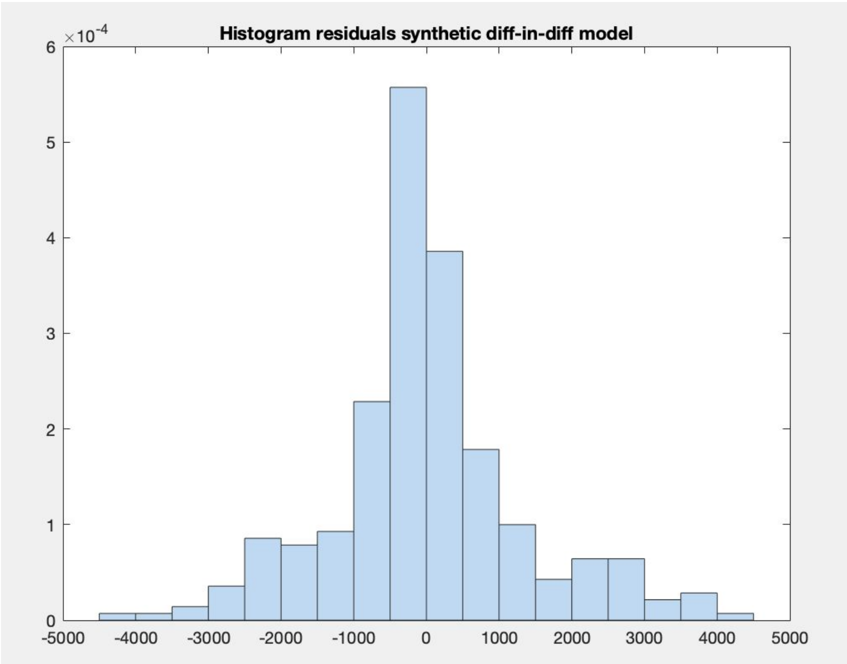

Figure 6.7 Raw residuals histogram of model 6

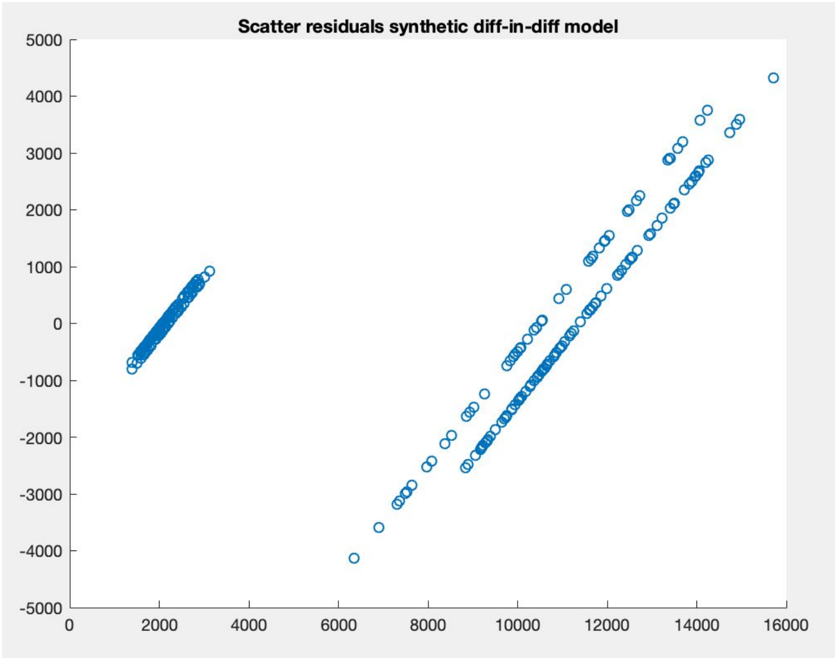

Figure 6.8 Raw residuals scatterplot of model 6

After refitting, we arrive at the final regression result (model 6.1):

Table 6.8 Difference-in-differences regression result of model 6.1 - Norway vs synthetic Norway constructed from 24 donors excluding Sweden (adjusted)

```
Linear regression model:
    production ~ 1 + group + time + NORtreatment

Estimated Coefficients:
                    Estimate      SE        tStat         pValue
                    ________    ______    ________    ___________

    (Intercept)      2200.6     138.36      15.905     9.7044e-40
    group            8337.8     233.42      35.721    9.2358e-100
    time            -118.78     170.68    -0.69595        0.48711
    NORtreatment     724.59     274.14      2.6431      0.0087385


Number of observations: 252, Error degrees of freedom: 248
Root Mean Squared Error: 959
R-squared: 0.956,  Adjusted R-Squared: 0.955
F-statistic vs. constant model: 1.78e+03, p-value = 1.78e-167
```

Whilst the statistical significance of the parameters remain unchanged, the coefficient of determination has improved to 95.5%. We hereby conclude on the result of model 6 and 6.1 that the Electricity Certificate scheme indeed has a positive significant impact on the hydroelectricity production of Norway. In detail, the certification scheme appears to prompt hydroelectricity power plants in

Norway to produce 724.59 GWh more than that of synthetic Norway which did not receive the incentive.

6.3 Robustness tests

We run several model deviations to check for the robustness of our main models. The details are well explained in Appendix 2, yet there are several noticeable findings as below:

If treating Sweden as a data replica for the original Norway, the results become either less insignificant or low power, both of which might be explained by the fundamental differences, especially in the shares of hydroelectricity and wind power, between the energy portfolios of Norway and Sweden.

Grouping Norway and Sweden into a common treatment region leads to significant positive parameters of interest, i.e. the Electricity Certificate Scheme has a similar positive impact on the hydroelectricity production of the joint market.

The synthetic control method repeatedly reinforces our initial conclusion that the electricity certificate scheme has a positive impact on Norwegian hydroelectricity production in models run on interpolated and extrapolated datasets. The weight vector slightly changes depending on the extent we apply interpolation, yet the core donors remain the same.

Overall, robustness tests succeed in proving the validity of our main models and hence the significant impact of the Electricity Certificate Scheme on the production of Norwegian hydroelectricity.

7 Further discussion

In this section, we would like to provide results and respective interpretation of auxiliary analysis, outline several shortcomings with their consequences on our work and draw possible extensions on ground of our master thesis.

7.1 Auxiliary analysis: Ordinary Least Squares Regression (OLS)

Topics of variables impact on new production and capacity of renewable-based electricity under the Electricity Certificate Scheme in Norway have been analyzed additionally through linear regression models. This analysis is preliminarily carried out with an aim to derive the impact of the Electricity Certificate Scheme on the ongoing expansion and operation, or development in short, of renewable energy power plants in Norway. We took interest in power plants' concessions, i.e. the right for a specific power station to be built and operated. As stated on NVE's website, "Licenses issued by the NVE are given to specified companies, granting them the right to build and run power installations and accessories as specified in the license. The license also states conditions and rules of operation." Important features of power station licensing taken into account are the applied capacity (MW), the applied output (GWh) and the year of authorization. To be more precise, we would like to extract the impact of the Electricity Certificate Scheme, featured by several independent variables such as the certificate prices, quotas and cancellations, given other related control variables specified in Data Description, on the licensed renewable power plants' capacity and output.

Regarding the methodology, OLS is a type of linear least squares method for estimating the unknown parameters in a linear regression model. The OLS principle yields an estimator that minimizes the squared differences between the observed values of dependent variables and predicted values from the estimated model (Vogelvang, 2005, p.55). This is among the most frequently used and most easily applied empirical tools to derive the strength and characteristics of the relationship between one dependent variable and a series of independent variables. All these characteristics make OLS stand out to be the most appealing method to employ in this analysis as we expect to formalize the relationship between the Electricity Certificate Scheme and power production licensing.

7.1.1 Application of OLS model and its specification

As mentioned in Data Description, we set up linear regression models to include four categories of key independent variables. The first two models, with Y_t be either authorised expected production (Y_t^P) or applied capacity of a prospective power plant (Y_t^C), incorporates all variables of interest as follows:

$$Y_t = c + \alpha_1 ELP + \alpha_2 ELQ + \alpha_3 ELC + \beta_1 ETAX + \beta_2 EMI$$

$$+ \gamma_1 EP + \gamma_2 EC + \gamma_3 GR + \theta_1 GDP + \theta_2 UNEM + NO1 + NO2 + NO3 + NO4 + \varepsilon_t$$

Description of the independent variables are presented in Appendix 1 (see table A1.3). c is the constant term associated with the regression model while ε is the error term. We use the timing index $t = 1, 2, ..$ according to the available data on monthly renewable power plant concession.

The parameters' statistical significance helps us adjust our model and study certain sets of variables' collective effect on the dependent variables.

7.1.2 Results and discussions

Under the Electricity Certificate Scheme, there's a significant increase in new production and capacity of renewable-based electricity in NO4 (Northern Norway). Moreover, capacity of renewable-based electricity power plants is significantly and positively correlated with the quantity of Electricity Certificates and negatively correlated with grid rent, emissions and GDP. Last but not least, the cost of certification has a significant but not apparently negative effect whilst environmental tax has a significantly positive effect on production and capacity of renewable-based electricity. In other words, certificate prices are not the fundamental factor that affect the renewable-based electricity development in Norway under the said scheme. Results from other models (model 16 - 20) we have run under the topics are with low R-squared value. Therefore, they will only be attached in the appendix (see Appendix 1, table A1.2) without further elaborations.

The model interpretation above adds to our main results in the sense that it expands the research scope into prospective production rather than past and current production only. Although the outcome is not as significant as we expect, the idea of broadening the analysis scope on Norwegian renewable energy production is invaluable to our thesis. Furthermore, the regression also enriches our analysis in the geographical aspect, pointing out the importance of location in the process of applying for new renewable energy production sites. Finally, statistical significance of various control variables in our regression models not only reaffirms previous findings in the literature regarding the effectiveness of certification on renewable energy but also signals potential future research orientations.

7.2 General shortcomings

Using data with higher frequency than monthly frequency in our dataset would serve the study purpose better. However, due to the fact that hourly, or daily data to some independent and dependent variables can not be retrieved, monthly data, as the next best sequential frequency that allows for running diff-in-diff regression models in both intra-national and international analysis is chosen to serve the study purpose.

Few observations in the dataset is technically not optimal to run regressions on in order to answer the studies. 576 observations from national monthly production data of hydro, thermal and wind power plants in Norway in the period between 2004 and 2019 are deployed in the DiD regression models in the intra-national analysis. Moreover, after completion of international analysis, we conclude the results from model 6 and 6.1 because of their better explanation power and significant results. However, according to table 2, numbers of observation to model 6 and 6.1 are 280 and 252 between 2008 and 2019. Although conclusion from few observations might be less reliable, we cannot refrain from doing so in order to arrive at better fit models.

Higher regression explanation power might be offsetted by an even smaller sample-size dataset. Scattering the raw residuals of each model as one of two residuals analysis had been performed as a part of the intra-national analysis.

Heavily influential outliers that had been identified are omitted from the original dataset, thus improving the regression´s explanation power.

Another possible cause for the aforementioned shortcomings is the time frame of the dataset. In our thesis, the result of model 7 and 8 stating that the scheme of interest does not have a significant effect on the Swedish hydroelectricity production, which is previously explained by different energy portfolios, is based on the dataset with a time frame between January 2008 and December 2019. However, the scheme was introduced in Sweden in May 2003, and our thesis does not take the Swedish hydroelectricity production between May 2003 and December 2007 into account when inferring the impact of such certification scheme to Swedish hydroelectricity production. Therefore, we can only conclude in this thesis that the Electricity Certificate Scheme has insignificant effect on the Swedish hydroelectricity production between 2008 and 2019, but not under the whole scheme implementation period.

7.3 Potential extensions

Because of the limitation in the time frame adopted in the thesis, a useful extension of this analysis in the future would be to determine whether Swedish hydroelectricity production is significantly associated with the scheme during the implementation period from 2003 up to present. Future research could also seek to forecast what is the final production of green electricity in Norway and Sweden given such incentives at the end of 2020 and 2035. In addition, empirical research of the regional effect of the Electricity Certificate Scheme on new renewable-based electricity production in NO4 electricity price areas (North - Middle Norway under geographical context) would become subject of interest to investigate.

8 Conclusion

This thesis examines the efficacy of the Electricity Certificate Scheme on the development of renewable energy in Norway. Our empirical work is backed by and further evidences the existing literature regarding the role of tradable green certificates in particular and renewable-incentivizing policies. For instance, findings from Nielsen and Jeppesen (1999) and Drahokoupil (2013).

We perform two main econometric methods in our analysis. First, DiD analysis is carried out on Norwegian hydroelectricity, wind power and thermal power production in the period from January 2004 to December 2019, a sample size of 192 months. Afterwards, we advance our analysis to synthetic control method adopted from Abadie, Diamond, and Hainmueller (2010) with the panel data of electricity production from 27 European countries across a 144-month timespan from January 2008 to December 2019.

The Electricity Certificate Scheme is proven to have a positive effect on hydroelectricity production on both intra-national and international levels while the scheme's influence on Norwegian wind power production is inconclusive. We attribute such differences in the Electricity Certificate Scheme performance to the fact that wind power in Norway is not as fully developed and mature as hydro power.

Short data timespan, resulting in small sample size, is an evident limitation of this thesis. Older historical data of renewable energy production is unavailable in public resources and hence leads to a lack of comprehensiveness in our conducted research when compared to other research such as Zhao et al. (2013) and Unger & Ahlgren (2005). This shortcoming prompts us a possible research expansion in which a richer dataset of renewable energy production in Sweden before and after 2003 is taken into account to overcome few-observation problems.

By conducting additional regression analysis, we see evidence of regional effects of the Electricity Certificate Scheme on new green electricity production in Norway. Rigorous research, therefore, could be implemented in this direction.

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Appendix 1

Table A1.1 Description and results of the auxiliary analysis

Model scope	Model number	Description
Auxiliary Analysis	14	Variables impact on output in concession of new renewable plants approved by NVE under TGC period
	14.1	Variables impact on output in concession of new renewable plants approved by NVE under TGC period (adjusted)
	14.2	Variables impact on output in concession of new renewable plants approved by NVE under TGC period (2nd adjusted)
	15	Variables impact on capacity in concession of new renewable plants approved by NVE under TGC period
	15.1	Variables impact on capacity in concession of new renewable plants approved by NVE under TGC period (adjusted)
	16	TGC variables impact on output in concession of new renewable plants approved by NVE under TGC period
	17	Other-than-TGC variables impact on output in concession of new renewable plants approved by NVE
	17.1	Other-than-TGC variables impact on output in concession of new renewable plants approved by NVE (adjusted)
	17.2	Other-than-TGC variables impact on output in concession of new renewable plants approved by NVE (2nd adjusted)

Table A1.2 Auxiliary regression analysis table (P-values in brackets)

Variables	Model 14	Model 14.1	Model 14.2	Model 15	Model 15.1	Model 16	Model 17	Model 17.1	Model 17.2
ELP	-8.2129 (0.13019)	-4.8693 (0.21081)		-2.4023 (0.1322)	-1.4133 (0.21624)	-0.9137 (0.72006)			
ELC	-0.0063041 (0.0088737)	-0.006906 (0.0076655)	-0.0028854 (0.063855)	-0.001844 (0.009203)	-0.0020108 (0.0081522)	-0.00028745 (0.012754)			
ELQ	2.9667e+05 (0.0086767)	3.4291e+05 (0.006125)	1.4147e+05 (0.051991)	86771 (0.0090061)	99873 (0.0065178)				
ETAX	4.6925 (0.0098292)	4.8735 (0.011158)	2.0862 (0.085417)	1.3726 (0.010184)	1.4183 (0.01185)		0.025735 (0.02214)	0.0066253 (0.13114)	0.0063748 (0.14441)
EMI	-606.72 (0.021612)	-470.6 (0.025926)	-236.24 (0.19675)	-177.5 (0.022243)	-136.89 (0.027294)		30.715 (0.15758)		
EP	0.81618 (0.62157)	-0.1159 (0.92127)		0.23382 (0.63059)	-0.040476 (0.90648)		-0.23614 (0.14528)		
EC	-2.3544e-05 (0.57971)	3.638e-05 (0.30118)		-6.9056e-06 (0.58074)	1.0642e-05 (0.30329)		-7.8965e-06 (0.3721)		
GR	-567.12 (0.085565)	-819.99 (0.043925)	-239.18 (0.25192)	-165.21 (0.088407)	-237.87 (0.046442)		-25.999 (0.12442)		
GDP	-0.23656 (0.010286)	-0.23723 (0.011896)	-0.10631 (0.081271)	-0.069198 (0.010655)	-0.06903 (0.012631)		-0.00056702 (0.45435)		
UNEM	-197.26 (0.50934)	-142.65 (0.50411)		-57.157 (0.51558)	-40.809 (0.51532)		103.99 (0.0012222)	69.424 (0.0095346)	68.799 (0.010023)
NO1	-91.171 (0.61581)	-92.781 (0.47783)		-25.553 (0.63243)	-25.826 (0.50107)		14.3 (0.83028)		
NO2	127.72 (0.30372)	17.463 (0.85249)		38.677 (0.2899)	6.4316 (0.81575)		48.159 (0.30668)		
NO3	172.2 (0.23591)	92.94 (0.38703)		51.866 (0.22511)	28.648 (0.36455)		83.209 (0.071365)	24.699 (0.45147)	
NO4	439.56 (0.019985)	432.82 (0.0018662)	342.45 (0.026643)	130.57 (0.018892)	128.66 (0.0016885)		123.34 (0.030861)	59.588 (0.20726)	49.962 (0.27084)
R-squared	0.53	0.738	0.352	0.531	0.739	0.197	0.202	0.106	0.103
Number of observations	41	38	41	41	38	41	138	138	138

Table A1.3 Explanatory variables

Variable	Meaning	Unit
ELP	electricity certificate price	NOK
ELQ	electricity certificate quota	percentage
ELC	electricity certificate cancellation	certificates
ETAX	environmental taxes	million NOK
EMI	GHG emission	Tonnes CO2 equivalent per mil NOK
UNEM	unemployment rates	percentage of population aged 15-74
GDP	GDP per capita	NOK per capita
GR	grid rent excl tax	øre/KWh
EP	Electricity day-ahead average price (on Nordpool)	NOK/MWh
EC	Net consumption of electricity per month	MWh
NO1	Electricity region NO1 (on NVE map)	dummy
NO2	Electricity region NO2 (on NVE map)	dummy
NO3	Electricity region NO3 (on NVE map)	dummy
NO4	Electricity region NO4 (on NVE map)	dummy

Appendix 2

A2.1 Model overview

We hereby provide a table of model overview with the number of models and its description. Our main models for intra-national DiD analysis are number 2 and 4, while those for international synthetic control analysis are number 6 and 6.1. "Adjusted" models have been under diagnostics and revision to improve their statistical interpretation.

Table A2.1 Model overview

Model scope	Model number	Description
Intra-national	1	Hydro vs Thermal
	2	**Hydro vs Thermal (adjusted)**
	3	Wind vs Thermal
	4	**Wind vs Thermal (adjusted)**
International	5	Norway vs 25 European countries
	5.1	Norway vs 25 European countries (adjusted)
	6	**Norway vs 24 European countries (excl. Sweden)**
	6.1	**Norway vs 24 European countries (excl. Sweden) (adjusted)**
	7	Sweden vs 25 European countries
	7.1	Sweden vs 25 European countries (adjusted)
	8	Sweden vs 24 European countries (excl. Norway)
	8.1	Sweden vs 24 European countries (excl. Norway) (adjusted)
	9	Norway and Sweden vs 24 European countries
	9.1	Norway and Sweden vs 24 European countries (adjusted)
	10	Norway vs 25 European countries (ARMA extrapolation)
	10.1	Norway vs 25 European countries (ARMA extrapolation) (adjusted)
	11	Norway vs 25 European countries (ARMA extrapolation) (excl. Sweden)
	11.1	Norway vs 24 European countries (ARMA extrapolation) (excl. Sweden) (adjusted)
	12	Norway vs 26 European countries (ARMA & linear interpolation, incl. Croatia and Iceland, excl. Sweden)
	12.1	Norway vs 26 European countries (ARMA & linear interpolation, incl. Croatia and Iceland, excl. Sweden) (adjusted)
	13	Norway vs 25 European countries (ARMA & linear interpolation, incl. Croatia only, excl. Sweden)
	13.1	Norway vs 25 European countries (ARMA & linear interpolation, incl. Croatia only, excl. Sweden) (adjusted)

Table A2.2 shows the DiD regression results from all models mentioned above. In this table, not only the variable of interest (α_3 and β_3) which presents the real effect of the electricity certificate scheme on renewable energy production but also its significance (proven by its P-value), the respective model's predicting power (indicated by R^2) and the number of observations are reported. Main models are highlighted in bold.

Table A2.2 Regression results for all models

Model	Variable of Interest (real effect of EL scheme)	P-value	R^2	Number of Observations
1	8.88E+05	0.001271	0.942	384
2	**3.69E+05**	**0.039572**	**0.977**	**334**
3	1.04E+05	6.02E-06	0.35	384
4	**-8233.9**	**0.53528**	**0.64**	**354**
5	1102.2	0.0035785	0.779	280
5.1	829.49	0.015219	0.834	259
6	**1009**	**0.0028648**	**0.92**	**280**
6.1	**724.59**	**0.0087385**	**0.956**	**252**
7	-240.62	0.32714	0.0745	280
7.1	-387.98	0.10392	0.0727	260
8	35.386	0.86948	0.633	280
8.1	-50.272	0.80065	0.723	255
9	1229.6	0.01574	0.918	280
9.1	1037.4	0.01191	0.953	253
10	1091.8	0.0033457	0.783	288
10.1	894.8	0.0082081	0.837	266
11	1027.2	0.0020384	0.922	288
11.1	753.68	0.005903	0.956	260
12	874.66	0.0084175	0.927	288
12.1	601.1	0.027386	0.959	260
13	1027.2	0.0020384	0.922	288
13.1	753.69	0.0059028	0.956	260

Respective weight vectors of the donor pool are in table A2.3.

Table A2.3 Weight vectors of synthetic control models

Model	5	6	7	8	9	10	11	12	13
Country									
Belgium	0.0000	0.0000	0.0134	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000
Bulgaria	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Czechia	0.0000	0.0000	0.0096	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000
Denmark	0.0000	0.0373	0.0000	0.0000	0.0000	0.0000	0.0373	0.0845	0.0373
Germany	0.0000	0.0000	0.0360	0.0445	0.0001	0.0000	0.0000	0.0003	0.0000
Estonia	0.0000	0.0000	0.0014	0.0000	0.0003	0.0000	0.0000	0.0002	0.0000
Ireland	0.0000	0.0000	0.1784	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000
Greece	0.0000	0.0000	0.0006	0.0000	0.0001	0.0000	0.0000	0.0001	0.0000
Spain	0.0000	0.0000	0.1462	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000
France	0.0000	0.0000	0.0039	0.1185	0.1843	0.0000	0.0000	0.0003	0.0000
Croatia	//	//	//	//	//	//	//	0.0000	0.0000
Italy	0.0000	0.0000	0.0010	0.0000	0.5530	0.0000	0.0000	0.3199	0.0000
Latvia	0.0000	0.0000	0.0004	0.0000	0.2567	0.0000	0.0000	0.1429	0.0000
Lithuania	0.0000	0.0000	0.0204	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000
Luxembourg	0.0000	0.0000	0.0174	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000
Hungary	0.0000	0.0000	0.0036	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000
Netherlands	0.0000	0.0000	0.0010	0.0000	0.0001	0.0000	0.0000	0.0002	0.0000
Austria	0.0000	0.4465	0.0447	0.7401	0.0000	0.0000	0.4465	0.0006	0.4466
Poland	0.0000	0.0000	0.0023	0.0000	0.0001	0.0000	0.0000	0.0002	0.0000
Portugal	0.0000	0.0000	0.0240	0.0000	0.0000	0.0000	0.0000	0.0004	0.0000
Romania	0.0000	0.0000	0.0075	0.0000	0.0001	0.0000	0.0000	0.0002	0.0000
Slovenia	0.0000	0.0000	0.0000	0.0000	0.0016	0.0000	0.0000	0.0002	0.0000
Slovakia	0.0000	0.0000	0.0087	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000
Finland	0.0000	0.5161	0.0009	0.0969	0.0034	0.0000	0.5161	0.1827	0.5161
Sweden	0.0000	//	//	//	//	0.0000	//	//	//
UK	1.0000	0.0000	0.0037	0.0000	0.0001	1.0000	0.0000	0.0003	0.0000
Iceland	//	//	//	//	//	//	//	0.2656	//
Norway	//	//	0.4747	//	//	//	//	//	//

A2.2 Robustness tests' results

Switching the analysis to Sweden for robustness check purposes, model 7, 7.1, 8 and 8.1 return either insignificant results or extremely low model power. The weight vector for model 7 is highly biased towards Norway, which replicates the initial problem of including a similar country in the donor pool as in model 6. Overall, the electricity certificate scheme does not have a solid effect on Swedish hydroelectricity production. This inconclusive outcome may be explained by the fundamental differences between the energy portfolios of Norway and Sweden. While in Norway more than half of expected normal annual production of renewable electricity plants included in the 28.4 TWh target is from hydro power plants, wind farms production dominates in Sweden (Swedish Energy Agency and NVE, 2018, see figure A2.1). Such differences may lead to asymmetrical results, especially when we only take hydroelectricity production into account.

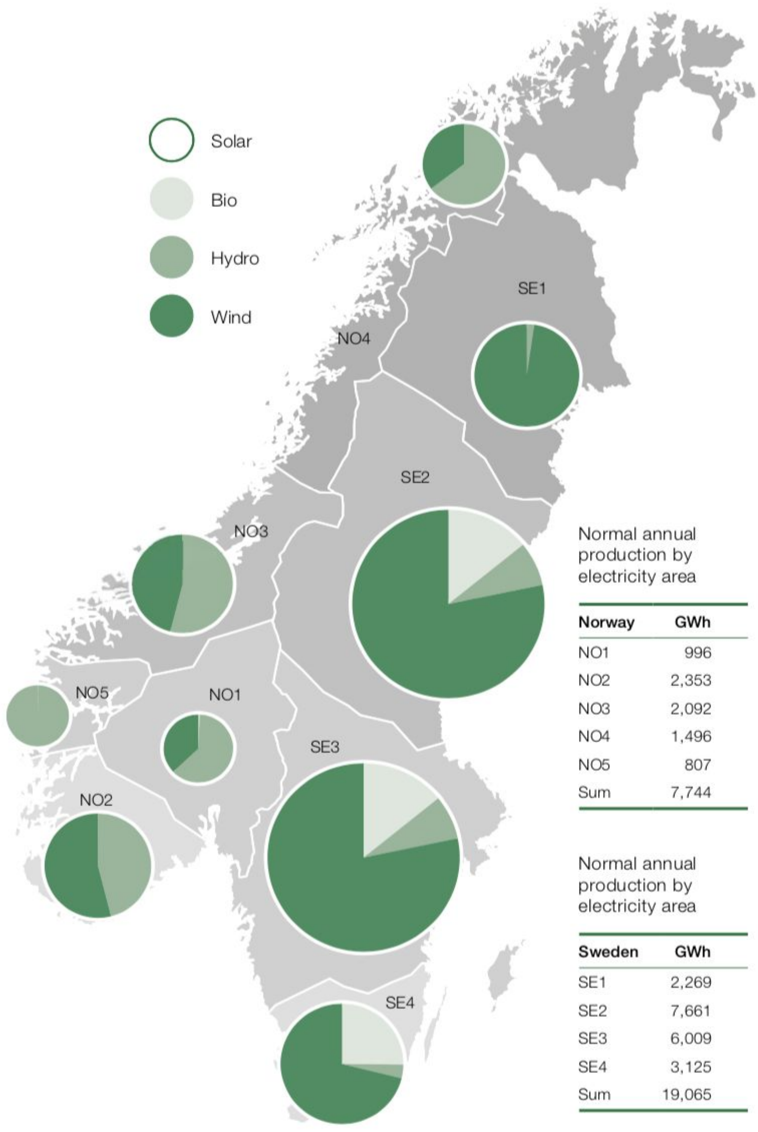

Figure A2.1 Normal annual production of plants included in the 28.4 TWh target by Elspot area

(Source: NVE)

Furthermore, we group Norway and Sweden together to form a treatment region in order to study the general effect of the electricity certificate scheme on the joint market of Norway and Sweden. The significant positive results are shown in model 9 and 9.1 with relatively high model power. The synthetic control method repeatedly proves the expected positive impact of the certification scheme on hydroelectricity production of the member countries. However, we keep in mind that given the previous electricity production source finding we discover, there is a possibility that such significant results might be predetermined due to the overwhelmingly large hydroelectricity production of Norway.

After forecasting end-of-period missing observations with the ARMA(2,1) model, we run model 10, 10.1, 11 and 11.1. These models' significance and weight vectors are similar to those of model 5 and 6. The consistent results from two models show that few extrapolations appear not to have a considerable impact on the overall results.

Expanding interpolation scope to linear forecasting, we have a chance to incorporate Croatia and Iceland into our models. We remain our exclusion of Sweden based on the same line of reasoning aforementioned. Regression result for model 12 reassures the consistency in the positive effect of electricity certificate scheme on hydroelectricity production while the synthetic control weight vector allocates the majority of weights to Italy, Iceland, Finland, Latvia and Denmark. Such results seem reasonable as we assume that those donors share the comparable hydroelectricity intensity and infrastructures with Norway.

Taking a closer look at Icelandic data, we realize that it contains numerous observations with 0 values from 2008 to 2010, which may happen due to EuroStat's statistical errors in the process of collecting data. By combining this shortcoming with missing data points in between the time series of Iceland as reasoning, we choose to remove Iceland again from our dataset to avoid biased results. This step helps us come up with model 13 whose significance and weight vector are homogenous to those of our main models (model number 6 and 6.1). It reinforces our initial conclusion that the electricity certificate scheme has a positive impact on Norwegian hydroelectricity production.