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Assessing the effectiveness of the 2011 feed-in tariff policy for wind power in Finland

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Abstract:

In 2011, Finland implemented a feed-in tariff in order to accelerate investments in wind power production throughout the country, since the wind power industry was not meeting the target production volume. The Finnish feed-in tariff stopped accepting new wind power projects into the scheme in 2017, and this study performed an analysis of the overall effectiveness of the feed-in tariff by aiming to answer the question: *"Did the feed-in tariff implemented in 2011 enhance the deployment of wind power in Finland and to what extent?"*. By employing an econometric approach using binary and difference-in-difference models, the effect of the feed-in tariff and other factors associated with wind power deployment were estimated. In the obtained results, the feed-in tariff displayed a large positive relationship to the amount of nominal wind power in a region. This research contributes to the existing literature by providing insights into the effectiveness of the wind power feed-in tariff in Finland, where such analysis has not been conducted so far, while also comparing the obtained results to those found in other countries.

Key words: Wind power, Renewable energy, Feed-in tariff, Renewable energy policy, Panel data models, Difference-in-difference, Finland

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Table of Contents

1. Introduction

Renewable energy has become increasingly important during the past two decades as concerns about greenhouse gas emissions and the dependence on fossil fuels have been raised, and as countries are looking for ways to diversify their energy portfolios. The majority of the world's countries have adopted at least some renewable energy targets by 2020, reflecting a global shift towards cleaner energy (IRENA, 2015). While still being a relatively new energy sector, renewable energy provides many opportunities and incentives for designing more efficient and cost-effective technologies. One incentive is the aim of dominating the future energy technology markets (Lee & Huh, 2017), but job creation through the new technologies is also important (Eurostat, 2019). Having gained a status as a mainstream energy source by constituting more than a fourth of all global electricity generation in 2018, renewable energy supply is expected to keep increasing at a steady pace in the future (REN21, 2019; Choi et al., 2018). Electricity sector has the largest role in increasing the amount of renewable energy production, even though transport and heating and cooling, have also drawn increasing interest in the last years (Huh et al., 2014).

Wind power is globally the second most used renewable energy source after hydro power, which has lately become somewhat controversial due to its impacts on biodiversity and human resettlement (Power Technology, 2020). In 2018, wind power accounted for 24 percent and hydro power accounted for 54 percent of global renewable energy capacity (Power Technology, 2020). Wind power is one of the fastest growing renewable energy sources globally, and its production levels surpassed hydro power production in the European Union in 2018, with their production accounting for 36 percent and 33 percent, respectively, of all renewable energy in the EU (Eurostat, 2020). Large potential for generating more wind power exists, but along with the high costs, new onshore wind power projects often face opposition due to their impact on people living in close proximity to the turbines, natural scenery, and wildlife, such as birds and bats. Offshore wind power is generally more accepted and would provide optimal conditions for wind power generation, but the immensely high cost of building the turbines in the sea is the reason for the low number of offshore wind turbines worldwide (Companeo, 2020).

Renewable energy sources are typically at a disadvantage when compared to conventional energy sources due to their high costs, which is why government subsidy policies have been crucial in increasing the amount of renewable energy generation. Most countries have developed and implemented policies to support renewable energies such as feed-in tariffs, quota obligations on renewable energy production, auctions, production tax incentives and investment incentives (REN21, 2019; Resch et al., 2008). In Europe, government support policies have played a key part in increasing the renewable energy production in countries like Germany and Spain. Their success with renewable energy has made them an example for other European countries, with several of them having implemented similar subsidy policies to accelerate investment in renewable energy (Frondel et al., 2010)[1]. One of the most widely used policies to increase investment in wind power production is a feed-in tariff, which is a price-based policy that gives the producer of renewable electricity the right to sell their production to the electricity network and obtain a specific pre-determined price that is above the wholesale market price for electricity for a predetermined number of years (García-Alvarez & Mariz-Pérez, 2012). The feed-in tariff provides long-term security on the electricity prices for the renewable energy producers, therefore making investments in the renewable energy less risky and more attractive (Ukkonen, 2017).

One of the European Union countries that was quite late to implement large-scale renewable energy subsidy policies, and has therefore only recently started to produce significant amounts of wind power, is Finland. Even though Finnish wind power production is still low on a global scale, in quite a short period of time, wind power has drastically increased to cover nine percent of the total electricity generation in Finland in 2018 (Virtanen, 2019). One plausible explanation for this fast increase is the implementation of a feed-in tariff to promote investments in wind power projects in the country in 2011. To the best of my knowledge, no studies have performed econometric analysis on the effectiveness of the feed-in tariff on wind power investments in Finland. Therefore, the research question this thesis aims to answer is: *"Did the feed-in tariff implemented in 2011 enhance the deployment of wind power in Finland and to what extent?"*.

The analysis first examines what factors are associated with the probability that wind power projects receive the feed-in tariff using a binary model approach. Then, the main part of the analysis uses a difference-in-difference approach to isolate the effect the feed-in tariff had on

[1] Currently, China is the country with the largest wind energy capacity in the world with 221 GW installed capacity, followed by the United States (96.4 GW), Germany (59.3 GW), India (35 GW) and Spain (23 GW), (Economic Times EnergyWorld, 2019).

the amount of installed wind power capacity in Finland. By first performing the binary model analysis, the study is able to analyze other factors besides the feed-in tariff that are associated with higher wind power production, and to ensure that the main part of the analysis has internal validity and does not suffer from an endogeneity problem. In order to use econometric models to analyze these questions, a panel data set is used dividing Finland into the 19 official regions, covering the period between 2000 and 2017. The regional panel data set takes into consideration the individual characteristics of the areas where wind power plants are set up, such as the proximity to coast and regional GDP growth.

In order for wind power plants to be eligible to receive the Finnish feed-in tariff, they had to be newly built and have a minimum power of 500 kW. If these conditions were not fulfilled, the wind power plants did not qualify for receiving the feed-in tariff, which was the reason why wind power in some regions was left without the tariff. In addition, the Finnish government decided to exclude all wind power in Åland from receiving the feed-in tariff. Because of this division between areas where wind power was eligible for the tariff and areas where wind power was not eligible to receive the tariff, a difference-in-difference analysis can be used to estimate the effect the feed-in tariff had on the amount of wind power production.

Finland experienced a sharp increase in the amount of wind electricity produced after 2011 (see Figure 3), which is when the feed-in tariff was implemented. With the empirical evidence of the feed-in tariff's effectiveness in other countries (see Section 3.2), it is interesting to study whether the feed-in tariff was the main reason for the increase in wind power generation in Finland, i.e. whether it was an effective policy instrument to promote wind energy deployment. Effectiveness in this context refers to the extent to which the policy is able to trigger the introduction of new renewable energy generation or installed capacity (Ragwitz & Steinhilber, 2014).

This research contributes to the existing literature by providing insights into the effectiveness of the wind power feed-in tariff in Finland, where such analysis has not been conducted so far. Finland differs from other countries whose renewable energy policies are commonly analyzed, as it was lagging behind in the amount of wind power generation in comparison to most countries in Europe for the majority of the time period studied. In addition, this study contributes to studies in the field by employing econometric analysis, which has not been used to a large extent on studies analyzing feed-in tariffs. The dataset employed in this study also covers a longer period than the datasets used in most studies that analyze the effectiveness of renewable energy policy instruments. A long dataset covering the entire period during which Finland experienced significant levels of wind power production is able to take into account all trends and possible shocks the Finnish wind power industry might have experienced.

The results of this study imply that the feed-in tariff was able to incentivize new investments in wind power production to a large extent, therefore heavily increasing the amount of wind power in Finland. The feed-in tariff was therefore effective, but there are some implications that the tariff became very expensive for the Finnish government, meaning that it might not have been a cost-effective policy for increasing wind power production. Coastal proximity was also found to be associated with high levels wind power production. Another factor that has affected the growth of Finnish wind power is fast technological development in the industry, which has made wind power much more competitive against other energy sources. Unfortunately, technological development is difficult to measure, and hence, this analysis has not been able to estimate the extent to which it contributed to the increase in Finland’s wind power capacity.

Before the feed-in tariff was implemented in Finland in 2011, wind power production was supported by granting an electricity tax reduction on all electricity produced using wind power, and additionally, individual wind power projects could receive investment grants that were decided case-by-case. This study is limited in the sense that it is not possible to disentangle the effects of the tax incentive policy and investment grants on wind power used in Finland between 1997 and 2010, since data on specific wind power projects and the funding they received could not be found. The tax incentive was equally sized for all wind power producers, and its effects on increasing wind power investments is difficult to measure. Overall, wind power production in Finland remained low until 2010, suggesting that these policies were not effective in incentivizing large investments in wind power production. The implementation of the new feed-in tariff scheme in 2011 also suggests that the previous policies were not providing satisfactory increases in wind power capacity. Another limitation to the study is that the dataset is limited to yearly data instead of monthly data, which would have provided more observations and possibly improved the accuracy of the results. Monthly data would have been able to account for changes in energy production quantities, prices, GDP growth and so on, better than yearly average and cumulative data can. Nevertheless, the yearly variation in the variables is still visible and the number of observations is 342, which creates confidence in the obtained results.

The thesis is structured as follows. Section 2 presents the background to the Finnish energy market, with a focus on wind energy. Section 3 presents the theoretical framework and previous literature on renewable energy subsidy policies. Section 4 describes the data, variables, expected results, the empirical method, and the regression models. These are followed by the empirical results and sensitivity analysis in Section 5. Finally, Section 6 concludes the study with the major findings and analysis, and also presents ideas for future research on the topic.

2. Background

Finland's electricity production is heavily dependent on nuclear power and its share is expected to grow in the future as another nuclear reactor will be opened in the coming years. Hydro power and biomass generate the most electricity after nuclear power, both accounting for 19 percent of total electricity generation, and they are followed by wind power with nine percent and coal with eight percent (Finnish Energy, 2019). Finland is also quite dependent on imported energy, as net imported energy accounted for 23 percent of energy consumption in 2018 (Virtanen, 2019). However, Finland's dependency on imported energy is expected to fall due to increased renewable energy deployment (Aslani et al., 2014). An interesting feature of Finland's energy mix is that solar power, which has become a globally popular and trendy renewable energy source, only accounted for 0.2 percent of electricity production. Bureaucratic issues related to solar panel installations and lack of investment incentives have stalled solar power's entry to the Finnish energy market (LUT, 2019).

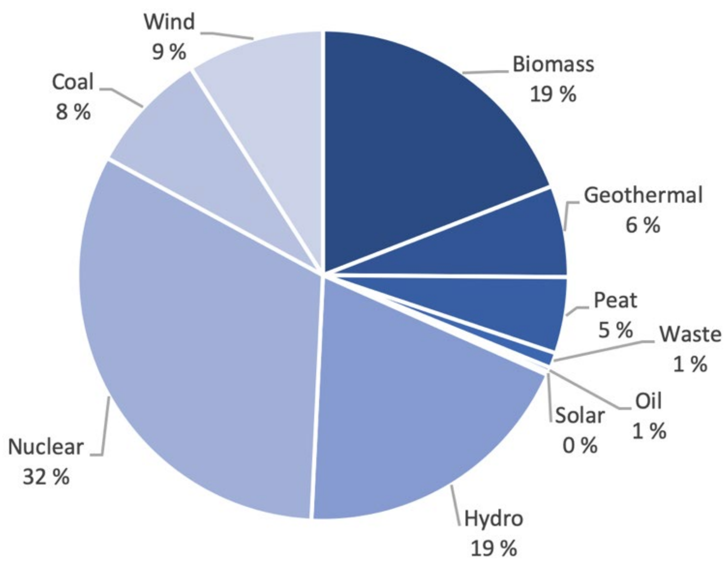

***Figure 1**. Electricity production by source (67 TWh in total). Source: Finnish Energy, 2019.*

Renewable energy constituted 47 percent of total electricity production in Finland in 2018, while 79 percent of electricity production was CO_2 neutral (Finnish Energy, 2019). Some of the pressure to invest in renewable energy comes from the EU, which has set ambitious targets for its gross energy consumption[2]. In accordance to the EU's renewable energy targets, the Finnish government set long-term climate and renewable energy strategies in 2008 and 2010 and set the goal for future wind power production to be increased from production of 400 GWh in 2010 to 6 TWh by 2020 (Tarasti, 2012). As wind power production was not profitable on its own, and since the electricity tax reduction and investment grants[3] on wind power used during 1997-2010 were not providing enough incentive for new investments in wind power, the government decided to incentivize new wind power projects through a feed-in tariff.

The feed-in tariff on wind power, biofuel, and biogas was implemented in 2011 with the aim of accelerating investments in them, increasing their competitiveness against other energy sources, and increasing the independence of the Finnish electricity market (Finnish Wind Power Association, 2019). The feed-in tariff on wind power was meant to cover approximately 40 percent of the investment costs of new wind power plants in Finland and it was set equal to 83.5 €/MWh. The wind electricity producer gains the difference between the tariff-payment and the current electricity market price, that is, if the electricity market price is equal to 35 €/MWh, the producer receives 48.5 €/MWh. In order to stimulate new investments in the beginning of the tariff scheme, wind power projects were eligible to receive a higher tariff of 105.30 €/MWh for the first three years, but only until the end of 2015 (Finnish Wind Power Association, 2019). The wind power plant receives the tariff for 12 years, even after the tariff scheme ended, which is expected to have a strong positive impact on the received profits, therefore lowering the risk on the large initial investments required to set up wind power plants or wind farms. A total of 125 new wind power plants were accepted to the tariff scheme between 2011 and 2017, which were enough to meet the goals set for Finnish wind power production by 2020 (Finnish Energy, 2020). Therefore, the feed-in tariff scheme stopped accepting new wind power projects in the end of 2017. Another reason the government did not choose to continue subsidizing new wind power projects was the large cost of the feed-in tariff scheme (Finnish Energy, 2017). Koistinen

[2] In 2009, the EU set a binding target that by 2020, 20 percent of the Union's energy needs must come from renewable sources and the current target raises this figure to 32 percent by 2030 (European Commission, 2020).

[3] The tax incentive provided to renewable electricity producers was a partial rebate on the electricity tax (equal to 0.69 €/KWh in 2006), while the investment grants on new wind power technology were given to cover up to 40 percent of the investment costs of new wind power plants and decided on a case-by-case basis (VTT, 2007).

(2017) claims that even though the feed-in tariff was able to stimulate investments in Finnish wind power, in hindsight, the tariff payments were set on a too high level, since it has been estimated that the tariff payments made to the wind power producers between 2017 and 2030 will cost around €3 billion to the Finnish government. Wind power production in Finland experienced low growth levels before 2011 but since 2014 the growth has been fast, as can be seen in Figure 3. It seems reasonable to assume that at least a part of the fast growth is due to the feed-in tariff on wind power. Another factor that has had a positive impact on the number of new wind power projects is the particularly fast technological development in the Finnish wind power industry, which has significantly lowered the production costs (Kyytsönen, 2018). Technological development in the wind power industry is difficult to measure, which is why this study cannot analyze its effect on new wind power projects in a more detailed manner.

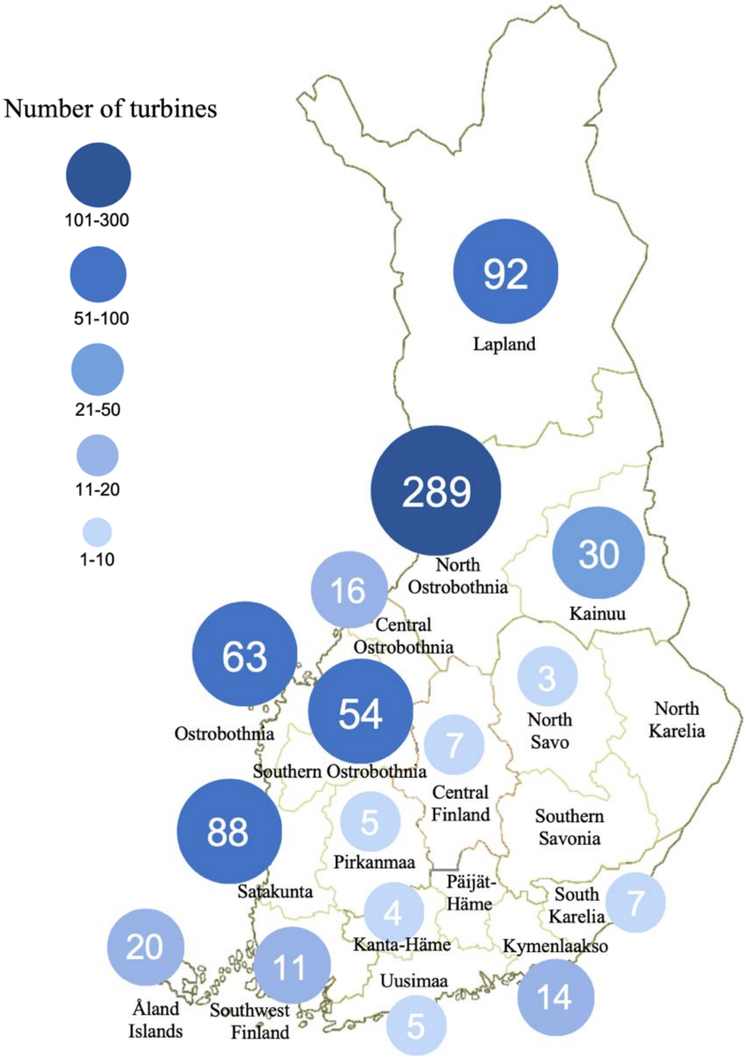

Figure 2. *Wind power plants by region. A larger and darker circle represents a higher number of active turbines. Source: Finnish Wind Power Association, 2020.*

The Finnish coastal and sea areas as well as the fjelds in Lapland are particularly favorable for wind energy generation, but as the technology develops, wind power generation is expected to spread more to the inland as well (Finnish Energy, 2019). Figure 2 displays the map of Finland divided into the 19 official regions with the number of wind power turbines in place in the end of 2017. The majority of the wind power plants are located along the Western coast of Finland, which is particularly favorable for wind power production when the wind blows from the Baltic Sea. Only three regions (North Karelia, Southern Savonia and Päijät-Häme) do not have any wind power production. These regions are all located inland where wind power production is less attractive due to lighter winds, which could explain the lack of wind power production.

3. Theoretical Framework and Literature Review

3.1 Subsidy Schemes for Renewable Energy

Increasing the amount of renewable energy is important in slowing down global warming, as renewable energy produces significantly less carbon dioxide emissions than fossil energy. However, the high capital and installation costs associated with renewable energy place it at a disadvantage compared to conventional fossil energy sources. In addition, investment in renewable energy has not been attractive due to market failures that have persisted in the energy markets across the world. The first and most important of them is that "the price of the production and consumption of power generated by fossil fuels does not reflect the costs they impose on others through climate change and local air pollution" (Curran et al., 2017). This implies that a price disparity exists between fossil fuel and renewable energy, and that the price of fossil energy does not compensate for the negative externalities they produce in the form of pollution. Other market failures creating obstacles for renewable energy are the access to networks, spillover effects from research and development (R&D), lack of economies of scale, and the enormous market power held by the mature energy sources and technologies (Stern, 2015; Dechezleprêtre, Martin & Bassi, 2016; LSE, 2018a; UCSUSA, 2017). Spillover effects from R&D can produce benefits to other firms in addition to the firm generating and investing in the R&D (Chen et al, 2013). This, in turn, might decrease the profitability of the R&D to the firm as they are not able to benefit from the R&D investments alone and could therefore even discourage investments in own R&D. The significance of R&D is particularly important in new industries where technological development is needed to improve the production efficiency and lower the production costs in order to gain market power. This has been the case in the wind power industry, as production of wind power has not been profitable on its own due to the high production costs. Technological development in the industry has been able to lower the cost of production and made the industry more profitable even without government subsidies (Kyytsönen, 2018). Another market failure creating obstacles for wind power is the lack of economies of scale, implying that as production amounts remain relatively low, producers are not able to benefit from the cost advantages that large-scale production is often able to provide. The high production costs decrease the profitability of wind power and make competing with the lower-cost conventional energy producers difficult. The market power held by the mature energy sector enables them to lower the energy prices to consumers, therefore making it difficult for the expensive wind power to compete with them. Renewable energy subsidy policies have been crucial in correcting for these market failures and increasing the amount of renewable energy globally by lowering the prices of renewable energy, increasing innovation, broadening the global energy mix, and lowering the dependence on polluting fossil fuels (LSE, 2018a).

The high subsidies given to renewable energy have been criticized, but interestingly, fossil fuel and nuclear power receive much higher amounts of financial support each year compared to renewable energy, $260 billion versus $140 billion in 2016 alone (Shirai & Adam, 2017). In addition to that, "the inflation-adjusted support for new energy sources is much lower today than it has been at any previous point in our history" (Pfund & Healey, 2011). The high subsidies given to renewable energy might soon be history, as technology has developed fast and is already becoming cost-competitive in some areas of renewable energy, meaning that subsidies have fulfilled their purpose and are no longer needed. It has been suggested that countries should move from subsidies to carbon pricing in the future, which would allow emission reductions in a more cost-effective way (LSE, 2018b)[4].

The two most used policy instruments to promote investments in new renewable energy are the feed-in tariffs and premiums (FIT) and quota obligations, but in recent years there has been a

[4] Carbon pricing refers to a cost applied to carbon being emitted in the production process, which would stimulate emission reductions. Particularly in the EU, economists agree on the high effectiveness of carbon pricing in emissions reduction (LSE, 2018a).

global shift from feed-in tariffs to competitive auctions[5] (REN21, 2019). A feed-in tariff or a feed-in premium on renewable energy production is a price-based policy and gives the producer of renewable electricity the right to sell their production to the electricity network and obtain a price that is above the wholesale market price for electricity. The price obtained by the subsidized producers can be based either on a fixed price, in the case of the feed-in tariff, or on a daily market price plus the additional subsidy, in the case of the feed-in premium (García-Alvarez & Mariz-Pérez, 2012). The FIT offers long-term security through the fixed payments to renewable energy producers, typically lasting between 10 and 20 years, which is why the European Commission determined it to be more effective and efficient than the tradable renewable energy credit (REC) system in 2005 (Rickerson & Grace, 2007). Other price-based policies include fiscal incentives, such as investment credit, tax reductions or exemptions, which exempt the producers of renewable energy from certain taxes. The effectiveness of them depends on the tax levels that prevail, and therefore they tend to be more effective in countries with high tax levels, such as the Nordic countries (European Commission, 2008).

Quota obligations, renewable obligations and renewable portfolio standards are quantity-based renewable energy market instruments, which impose an obligation on producers, suppliers or energy consumers to source at least a certain percentage in the energy mix from renewable sources. Quota obligations are typically facilitated by tradable green certificates (TGC), which are sold by producers of renewable energy and traded separately of the renewable energy itself (European Commission, 2008; KYOS, 2020). Auctions are another form of quantity-based policies, in which a government issues a tender for the provision of renewable energy from a certain technology source, and the lowest offer to complete the project is accepted (European Commission, 2008).

3.2 Findings from previous literature

Existing literature analyzing the effect of different government policies in promoting renewable energy production is vast. Several studies have compared different policy instruments but present varying results on their effectiveness, depending on the specifications of each individual study. Most published studies have, however, found that at least some policy instruments tend

[5] Despite the decrease in the popularity of the feed-in tariff, they were still in place in 111 countries in the end of 2018 (REN21, 2019).

to promote the deployment of renewable energy sources (Choi et al., 2018; Kilinc-Ata, 2016; Ragwitz & Steinhilber, 2014; Butler & Neuhoff, 2008; Haas et al., 2011; Bean et al., 2017).

Some studies provide results supporting the view that quota-based instruments display more signs of effectiveness while also being more efficient and have a lower risk than price-based instruments, such as feed-in tariffs, especially in the long run (Schmalensee, 2012; Ragwitz & Steinhilber, 2014; de Mello Santana, 2016). The variation in the results obtained by different studies is clear, as Kilinc-Ata (2016) presents opposite results suggesting that in the European and United States' energy markets, feed-in tariffs, tenders, and tax incentives are effective instruments in increasing renewable electricity capacity, but that quota-based instruments are not. Butler and Neuhoff (2008) obtain similar results from the United Kingdom and Germany, and Ertürk (2012) concludes that feed-in tariffs effectively generate an incentive for producers to invest in new wind energy plants in Turkey. In a study from South Korea, Choi et al. (2018) find that the feed-in tariff on wind power was economically more efficient from the government's perspective than the renewable portfolio standard. However, from the wind power producers' perspective, the feed-in tariff was less efficient than the renewable portfolio standard.

The success of feed-in tariffs is typically attributed to the more secure payments to energy producers occurring under the feed-in tariff than under the other instruments. These studies also found feed-in tariffs to be able to lower the cost to electricity consumers better than other instruments. However, not all studies agree on this either, as Bean et al. (2017) find an investment credit policy to be more cost-effective and involve a lower financial risk to consumers than feed-in tariffs and premiums in Spain.

Sometimes, the effectiveness of feed-in tariffs depends on the renewable energy they are subsidizing. For example, Jenner et al. (2013) find that feed-in tariff policies across EU have promoted the increase in solar photovoltaic capacity but find that feed-in tariffs have had no significant effects for onshore wind power generation in European Union countries between 1992 and 2008. The authors explain that this result can be due to the fact that wind power is a more mature technology than solar photovoltaic technology, and power generation costs for wind power are lower, providing an incentive to generate wind power even in the absence of the feed-in tariffs. Other studies shed light on the issues associated with feed-in tariffs and why they have not succeeded in stimulating investments in renewable energy. Frondel et al. (2010)

contradict many of the typical assumptions associated with renewable energy policies, the feed-in tariff in particular. Based on net present cost estimations, they argue that electricity provision through renewable sources has been very costly and therefore not a cost-effective way to perform climate protection in Germany. The authors also state that consumer prices of electricity have been increasing, technological process has been stifled and that even with large amounts of renewable energy, backup systems of fossil fuels need to exist. Di Dio et al. (2015) find that the highly complex Italian technical standards together with bureaucratic processes stifled the implementation of the feed-in tariff on solar power, therefore decreasing its efficiency in the country.

It is clear that there is no consensus over the most effective and cost-efficient policy to promote renewable energy, but the discussion over the efficiency of renewable energy support policies has been active. The success of the policy depends on the individual country's characteristics and the design of the policy, which is why there is no one policy to fit all countries' energy markets. Different methods of measuring and analyzing the effectiveness of different renewable energy support policies also seem to affect the results. Most of the studies presented in this section employ a cost-benefit analysis, net present value calculations, or similar methods (Frondel et al., 2010; Ragwitz and Steinhilber, 2014; Choi et al., 2018), while only some rely on econometric analysis (Ertürk, 2012; Jenner et al. 2013; Kilinc-Ata, 2016). With many different results on the success of the feed-in tariff and other renewable energy policies, it seems difficult to predict whether a particular policy will succeed in promoting investments in renewable energy. Feed-in tariffs and quota obligations are the two most used instruments, but in recent years there has been a global shift from feed-in tariffs to competitive auctions (REN21, 2019). Perhaps the shift away from feed-in tariffs is due to issues similar to those found by Frondel et al. (2010) and Di Dio et al. (2015). As Figure 3 suggests, the Finnish feed-in tariff was plausibly able to trigger new investments in wind power. The Finnish feed-in tariff on wind power was implemented quite late, and perhaps it was designed keeping in mind the reasons it has not been successful in some countries and correcting for those issues when fitting it to the Finnish energy market. However, as stated by Koistinen (2017), the policy turned out to be very costly for the Finnish government, which is also the reason why Frondel et al. (2010) stated the policy did not truly succeed in Germany.

4. Data and Empirical Method

4.1 Data

A panel data set was collected to analyze the research question at hand. The total dataset is strongly balanced containing data on all of the 19 official Finnish regions between the years 2000 and 2017. With panel data, the unmeasurable time-invariant characteristics of each region, such as the overall attitude towards wind power or the average amount of wind in the region (assuming that they do not change over time), can be held constant even though measuring them is not possible (Stock & Watson, 2015). As will be described later on, shorter versions of the dataset containing a shorter time period from 2007 until 2017 will also be used with the purpose of analyzing the sensitivity of the models and the robustness of the results. Unfortunately, data on 2018 was not accessible for all of the key variables, which is why the dataset is limited to end in year 2017. This should not create an issue for the analysis, however, as the Finnish feed-in tariff scheme on wind power was active during 2011-2017, and thus data from year 2017 contains all information on the final year during which new wind power projects were able to enter the feed-in tariff scheme.

The analysis divides the sample of 19 regions into two groups, the treatment group of 13 regions, where wind power plants start receiving the feed-in tariff at some point between years 2011 and 2017, and the control group consisting of six regions where wind power plants were not eligible to receive the feed-in tariff at any point. Based on Figure 2, the differences in the amount of wind power plants across the regions seem to mainly result from the differences in the conditions for wind power generation, as the majority of wind power plants were located near the coast in 2017. Therefore, one can assume that no other strong regional factors seem to heavily influence the placement of wind power. It is unfortunate that the division between treatment and control groups is not more equal, but real-world data often lacks perfection. However, as the dataset spreads from year 2000 until 2017, there is plenty of data on the treatment as well as the control group regions before the feed-in tariff was implemented in 2011, which helps to distinguish the differences that already exist between the treatment and control groups before the treatment, i.e. the feed-in tariff, begins.

The control group contains the following six regions: Åland Islands, Southern Savonia, Päijät-Häme, Pirkanmaa, North Karelia, and Uusimaa. The treatment group contains the following thirteen regions: South Karelia, Southern Ostrobothnia, Kainuu, Kanta-Häme, Central Ostrobothnia, Central Finland, Kymenlaakso, Lapland, Ostrobothnia, North Ostrobothnia, North Savo, Satakunta, and Southwest Finland. The regions are shown in the map of Finland in Figure 2. The southernmost region in Finland, Uusimaa, was expanded in 2011 when a region called Eastern Uusimaa joined it. Uusimaa and Eastern Uusimaa are treated as one uniform region in the dataset throughout the years 2000 until 2017. This measure is taken in order to simplify the dataset, but it should not significantly affect the results obtained from the regressions.

One important factor to note is that the Finnish government decided to exclude the Åland Islands from the feed-in tariff scheme despite the excellent conditions for wind power production in the Finnish archipelago (Suni, 2012). The arguments behind the decision were miscellaneous. On the one hand, the autonomous and self-governing status of the Åland Islands was given as a reason, while on the other hand, the high costs that the feed-in tariff posed to the Finnish government and the fact that Åland Islands already received more government funding in relative terms than any other Finnish region, were mentioned (Suomen Uutiset, 2015). The Åland Islands were among the first regions in Finland to set up wind power plants in the early 1990's, but due to the lack of financial support, the number of wind power plants in the Åland Islands did not grow at all between 2007 and 2017, even though plans for several new wind farms were underway (Lindqvist, 2016). Lindqvist (2016) argues that the number of wind power plants in Åland Islands would have surely increased since 2011 if the feed-in tariff had been extended outside of the Finnish mainland as well. Due to the fact that Åland Islands were not included in the feed-in tariff scheme, the region has been omitted from the dataset used for the probit and logit regressions. Åland's characteristics in the dataset are in line with all other regions that received the feed-in tariff (such as plenty of pre-existing wind power plants) and greatly differs from those regions where wind power was not eligible to receive the feed-in tariff funding (most of which have very little or zero wind power production), which is why including the Åland Islands in the dataset for the binary models could deteriorate the results. Including the Åland Islands in the panel data regressions and the difference-in-difference regressions is not a problem, however, as Åland acts mainly as one of the regions in the control group that does not experience growth in wind power production when FIT scheme is active on the Finnish mainland.

4.2 Variables and Expected Results

Dependent variables

The dependent variable for the panel data models is the combined nominal power of all wind power plants in megawatts (MW) in region i in a given year t, denoted by $power_{it}$. It represents the amount of wind power that can be produced in a region during a year. The panel data and difference-in-difference models try to find relationships that can explain the variation in the nominal power of regional wind power plants between years 2000 and 2017. In similar studies, the dependent variable is often wind power capacity or the amount of wind power relative to the whole country's energy production, meaning that this dependent variable is in line with previous studies. Data for the nominal power of wind power plants in different regions between years 2000 and 2017 were obtained from the Finnish Wind Power Association's database.

For the logit and probit models, the dependent variable is a binary variable representing the feed-in tariff status of a region in a given year, denoted as FIT_{it}. The variable takes on the value of 1 during the years when at least one wind power plant in a region received the feed-in tariff and zero otherwise. Since the feed-in tariff was implemented in 2011, the variable can only take on values of 0 for all regions before 2011. Data on the wind power plants accepted into the feed-in tariff scheme were obtained from the Finnish Energy Authority's official database.

Independent variables

The independent variables can be divided into four groups: substitute energy sources, security variables, economics variables and other regional characteristics. Substitute energy sources, i.e. hydro power, nuclear energy, and the total amount of electricity generated from all fossil fuel sources, have been included because of their expected impact on the deployment of renewable energy sources. Hydro power production is common across Finland, but the production amounts greatly differ between regions. Hydro power production, denoted as $hydro_{it}$, represents the total amount of hydro power production in region i during year t, measured in GWh/year. Nuclear energy, on the other hand, is only focused on two regions in Finland: Satakunta and Uusimaa.

Even though nuclear energy production is not relevant for many regions, it is important to control for it, especially since the amounts of energy produced using nuclear power are very large on the scale of the whole country's energy production. The variable $nuclear_{it}$ represents the production of nuclear power in region i during year t and is measured in GWh/year. The variable $fossilFI_t$ combines the total domestic electricity production from oil, coal, natural gas, other fossil sources and peat. As individual fossil energy sources and peat as sources of electricity are substitutes for wind power but not likely to be as direct substitutes as other renewable energy sources, they have been summed up into one variable. In 2017, fossil energy and peat covered 19 percent of total electricity production in Finland (Statistics Finland, 2020). Regional data on fossil energy and peat was not obtainable, which is why this data is in the form of yearly country-level data, measured in GWh/year. These three variables represent the most important domestic sources of electricity in Finland, and therefore their production magnitudes are expected to have an impact on the amount of new wind power capacity. The data for regional hydro power and nuclear power production were obtained from Finnish Energy's database and the data for fossil energy production were obtained from Statistics Finland's database.[6]

Previous studies have found an increase in electricity generated by substitute energy sources (such as nuclear power and hydro power) to have a negative effect on the amount of renewable energy produced (Kilinc-Ata, 2016; Marques et al., 2010). Their argument has been based on the reasoning that an increase in the amount of electricity produced through a substitute energy source will result in a decrease in the amount of electricity generated from a renewable power source. Additionally, the effect of other renewable energy on wind power can be also ambiguous. Based on previous empirical evidence, I hypothesize that the polluting substitute energy sources and nuclear power have a negative association with the amount of added wind power capacity, while hydro power has an ambiguous effect.

The explanatory variable called the security variable, i.e. net energy imports, denoted $netimportsFI_t$ and measured in GWh/year, is included in the panel data and difference-in-

[6] Another important substitute energy source is biomass, but detailed data on its regional production was not obtainable for the purpose of this study, which is why it has not been included in the analysis.

difference models as the amount of imported energy is expected to have an impact on the deployment of renewable energy (Dong, 2012), and more specifically, wind power in this case. Marques et al. (2010) found a positive relationship between the amount of energy imports and the deployment of renewable energy sources in a country, implying that a larger energy dependency in a country is a driving force for deployment for domestic renewable energy. As aforementioned, Finland is heavily dependent on imported energy, and thus, I hypothesize that there is a positive relationship between the amount of net energy imports and the amount of wind power deployed in Finland. The data for net energy imports was obtained from Finnish Energy's public database.

The independent variables categorized as the economics variables include regional GDP growth, average yearly electricity prices, and the change in yearly domestic electricity consumption, denoted GDP_{it}, $elprice_t$, and $elconsFI_t$. Previous studies have found that GDP growth has a positive association to wind power deployment as higher income countries are assumed to be capable of facing the high costs associated with renewable energy production (Kilinc-Ata, 2016; Marques, 2010; Jenner et al., 2013). Following this reasoning, it seems fair to assume that higher-income regions, or the regions whose economy is in a better order in Finland, could produce higher levels of expensive renewable energy such as wind power. On the other hand, most wind power projects in Finland are privately funded, implying that the economic condition of a particular region might not affect the decision whether a wind power plant is set up there. Since the correlation between regional GDP growth and wind power production is positive, the expected result is that GDP growth is positively associated with wind power production. The data for regional GDP growth is obtained from Statistics Finland's database. Electricity consumption is expected to have a positive effect on wind power deployment, since in theory, increased demand could be met with increased production of renewable energy. Marques et al. (2010) found this relationship to be positive. The data for average per capita electricity consumption in the whole country was obtained from Statistics Finland. The reason for including country-level data instead of regional data on electricity consumption is that regional data was not available for a large part of the sample period. Lastly, the expected effect of electricity price on wind power production is positive, as higher electricity market price would imply higher profits for the electricity producers. The average annual electricity prices had to be collected from various sources, since data for the whole time period from 2000 until 2017 could not be found. The data for average annual electricity prices was obtained from Fortum (years 2000-2003), Statistics Finland's database (year 2004), Nordpool (years 2005-2010) and the Finnish Energy Authority (years 2011-2017).

The independent variables representing the regional characteristics include coastal proximity, denoted by the binary variable $coast_i$, the number of wind power plants in a region, denoted by $plants_{it}$, and each region's treatment or control group status, denoted by the binary variable $treatment_i$. In the dataset, the binary variable $coast_i$ equals 1 if the region has coastline or its border is located within 50 km from the coast and 0 for all other regions. As previously described, the majority of wind power turbines are located on the coast or near it, and therefore it seems reasonable to make the assumption that the variable $coast_i$ will be significant and positive in the panel data models but also in the logit and probit models. The number of plants, denoted $plants_{it}$, is used as an explanatory variable in the logit and probit models as it is highly correlated (0.51) with the variable FIT_{it}, and therefore expected to be positively associated with the probability that a region's wind power plants receive the feed-in tariff. The data for FIT_{it} was obtained from the Finnish Energy Authority's public database. The $treatment_i$ variable is used in the difference-in-difference models in order to separate the treatment and control groups and to obtain the interaction term that isolates the effect of the feed-in tariff. The data for the $treatment_i$ variable is also obtained from the Finnish Energy Authority's public database.

Lastly, an interaction term is used in the difference-in-difference models to isolate the treatment effect for the treatment group and it is the main variable of interest when analyzing the effectiveness of the feed-in tariff. By only separating the control and treatment groups, one cannot isolate the actual treatment effect, which is the feed-in tariff's effect on the treatment group in this study, but instead only captures the differences that exist between the control and treatment groups. The interaction term is denoted as $treatment_i*startyear_{it}$ or $treatment_i*Y2017$, depending on the model. The variable $startyear_{it}$ represents the time period during which at least one wind power plant in a treatment group region received the feed-in tariff. It takes on the value 1 for the first year the feed-in tariff was applicable to the region and 1 all years after that[7]. The interaction term is always equal to 0 for the control group regions, since they do not receive the feed-in tariff. The version $treatment_i*Y2017$ is used for datasets that only include

[7] During the time period studied, none of the regions' wind power plants stop receiving the feed-in tariff after already having received it, meaning that the variable $startyear_{it}$ will not take on a value of 0 again after already taking on the value 1 for any of the regions.

the years 2010 and 2017. In these models, the binary variable *Y2017* is equal to 1 for the year 2017, and therefore controls for the period in the end of the feed-in tariff scheme, while also capturing the trend in nominal wind power that occurs between 2010 and 2017.

4.3 Descriptive Statistics

In order for the reader to get a better understanding of the data, descriptive statistics are presented below. The upper part of Table 1 describes the region-specific variables (excluding coastal proximity and the number of plants, which are presented in Figure 2) for the control group regions and the lower part for the treatment group regions. Table 2 describes the variables that are not region-specific: electricity produced from fossil sources, domestic average annual electricity consumption, average annual electricity prices, and annual net electricity imports. The average amount of nominal wind power differs by a large magnitude between the treatment and the control groups, and the maximum nominal wind power is very far apart between the two regions, with the control group's maximum being 21.99 GWh and the treatment group's being 863.23 GWh (both maximums are from the year 2017). In a similar way, average hydro power production is much higher in the treatment group than in the control group. Nuclear production is more equally divided between the two groups, with each group having one region that produces nuclear power. Lastly, an interesting observation is that the average regional GDP growth is noticeably higher in the treatment group than in the control group, 0.86 percent versus 1.30 percent. However, plotting the average GDP growth of the control and treatment group shows that they closely follow the same trends (see Appendix 1, table A1). The minimum GDP growth values in both control and treatment groups are from year 2009, representing the aftermath of the financial crisis. The standard deviation is also large for all variables presented below.

Table 1. Descriptive Statistics for the control and treatment groups.

Variable	Mean	Median	Standard deviation	Minimum	Maximum	Observations
$power_{it}$	4.17	0	6.98	0	21.99	108
$hydro_{it}$	219.88	36.00	302.36	0	991	108
$nuclear_{it}$	1308.63	0	2941.51	0	8166	108
GDP_{it}	0.86	1.21	3.88	-12.46	13.04	108
$power_{it}$	27.59	2.60	86.81	0	863.23	234
$hydro_{it}$	932.07	172	1351.51	2	6186	234
$nuclear_{it}$	1095.77	0	3804.77	0	14763	234
GDP_{it}	1.30	1.49	4.48	-12.60	13.28	234

Table 2. Descriptive Statistics of variables that do not vary across regions.

Variable	Mean	Median	Standard deviation	Minimum	Maximum	Observations
$fossilFI_t$	24814.98	24977	7828.18	12404	39827	342
$elconsFI_t$	84870.89	84917	2849.31	79169	90388	342
$elprice_t$	35.57	34.60	10.54	12.80	56.64	342
$netimportsFI_t$	13361.44	12664.5	4235.68	4852.0	20426	342

The covariance matrix is presented in Appendix 1 Table A2. High covariances are observed particularly for the number of plants and nominal wind power (0.79) and the number of plants and FIT, i.e. region's wind power plants receiving feed-in tariff in a given year, (0.51). These high covariances are intuitive and imply that regression results are likely to find some positive relationships between these variables. As could be seen from the map in Figure 2, coastal proximity and the number of wind power plants are also highly correlated (0.52), and this high correlation could pose some multicollinearity issues in the regressions, which is why these two variables will not be included in the same models. The number of wind power plants and hydro power production are also quite highly correlated (0.45), which could support the thought that some regions in Finland are more preferable for renewable electricity production. As assumed, electricity generation from fossil sources is negatively correlated with wind power production (-0.29), supporting the choice to include fossil electricity production in the regression models.

4.4 Econometric Strategy

This study applies an econometric framework to assess the effectiveness of the Finnish feed-in tariff on wind power used during 2011-2017. Effectiveness is an evaluation criterion commonly used to evaluate support schemes and policies. In the context of this study, effectiveness of a renewable energy policy measures the extent to which the policy is able to trigger the introduction of new renewable energy generation or installed capacity (Ragwitz & Steinhilber, 2014).

Prior to estimating the regressions, the data were analyzed to find sings of heteroscedasticity and serial correlation. The data showed signs of heteroscedasticity and serial correlation, which is common in panel data settings that collect data on the same individuals, or regions in this case, and during consequential years. If heteroscedasticity is present, the estimated OLS standard errors of can be inefficient leading to the estimated coefficient values being inefficient as well. Inefficient standard errors result in incorrect p-values in OLS regressions and thus affect the reliability of the inference one can make based on the data at hand. Serial correlation, on the other hand, implies that observations are correlated to lagged versions of themselves. It occurs especially when observations are not independent of each other but can also occur if the model is incorrectly specified. Serial correlation causes the estimated OLS coefficients to be biased, causing hypotheses testing to be unreliable. In order to correct for the issues heteroskedasticity and serial correlation might cause in the estimations, clustered standard errors were used throughout the analysis. Clustering is a commonly used method in panel data analysis and allows for heteroskedasticity and any kind of autocorrelation in panel data, therefore producing correct standard errors (Cameron & Miller, 2015). In order to mitigate the heteroskedasticity and serial correlation present in the dataset, clustering the data by regions is used throughout the estimations and the standard errors presented in conjunction with the coefficient estimates are robust clustered standard errors.

When choosing between the pooled ordinary least squares, fixed effects, and random effects specifications, the Breusch-Pagan Lagrange multiplier test and the Hausman test were used (test output in Appendix 1, tables A3 and A4). The Breusch-Pagan Lagrange multiplier test was used to differentiate between random-effects and pooled OLS approaches. The obtained test statistic suggested that a random effects approach fits the data better. The Hausman test of fixed effects versus random effects approach also suggested that the random effects approach would be a more appropriate choice instead of the fixed effect estimator. The random effects specification poses a strong assumption that the observed and unobserved characteristics of an individual are not correlated. This assumption is difficult, if not impossible to fulfill, possibly causing the random effects specification to produce biased results. Therefore, despite the results obtained from the Breusch-Pagan Lagrange multiplier test and the Hausman test, the analysis does not rely on the random-effects specification alone, but rather uses it as a robustness check of the models' performance between different specifications. If the pooled OLS, fixed effects, and random effects specifications all provide similar results, it is a good sign of the robustness of the results and provides support for the argument that the models are not sensitive to changes in the estimation methods.

When it comes to the binary models, conditional fixed effects, random effects, and population-averaged logit models as well as random effects and population-averaged probit models are estimated. Conditional fixed-effects cannot be used for probit models, "as there does not exist a sufficient statistic allowing the fixed effects to be conditioned out of the likelihood" (Stata, 2020). In logit models they allow controlling for time-invariant characteristics of an individual, independent of whether they are measured or not (Williams, 2018). The population-averaged model differs from the random effects and the fixed effects models in the sense that it averages over all the subjects in the dataset and instead of using parametric estimation, it uses moment assumptions and iteratively chooses the best coefficient estimate β to describe the covariates and the response (Hong & Ottoboni, 2017). Due to the benefits and restrictions of the fixed effect, random effect, and population-averaged models, all three will be estimated in order to inspect the robustness of the results.

The main analysis of the thesis relies on regression results obtained using a difference-in-difference approach. It is a quasi-experimental design that is used to estimate the effect of a treatment or intervention by comparing the changes in outcomes for two groups after the treatment takes place. The two groups are the control group, which does not receive the treatment, and the treatment group, which receives the treatment. The theory behind the difference-in-difference design is that prior to the treatment, the two groups have parallel trends, and by comparing the two groups after the treatment, we are able to isolate the causal effect of the treatment (Angrist & Pischke, 2008). As aforementioned, the treatment and control groups in this study are determined by the division of the 19 official Finnish regions into a group of regions where wind power plants are eligible for the feed-in tariff and to a group of regions where wind power is not eligible to receive the feed-in tariff (due to reasons mentioned in Section 1). Since the treatment in this study is the feed-in tariff, the treatment group consists of the regions where wind power is eligible to receive the feed-in tariff and the control group consists of the other regions. In order to be able to isolate the causal effect and ensure the internal validity of the model, a critical assumption of parallel trends between the control and treatment groups must be fulfilled. There is no statistical test for the parallel trend assumption, but often simply plotting the data helps to determine whether the assumption is fulfilled or not (Angrist & Pischke, 2008). If the assumption is not fulfilled, the estimate of the treatment effect will suffer from a bias. Figure 3 suggests that the assumption of parallel trends between the treatment and control groups prior to the treatment is fulfilled.[8]

[8] The slight difference in the trends that can be observed for the year 2010 could be due to the fact that some wind power producers were already prepared for the implementation of the feed-in tariff in 2011 and had started to increase wind power capacity in the end of 2010 already.

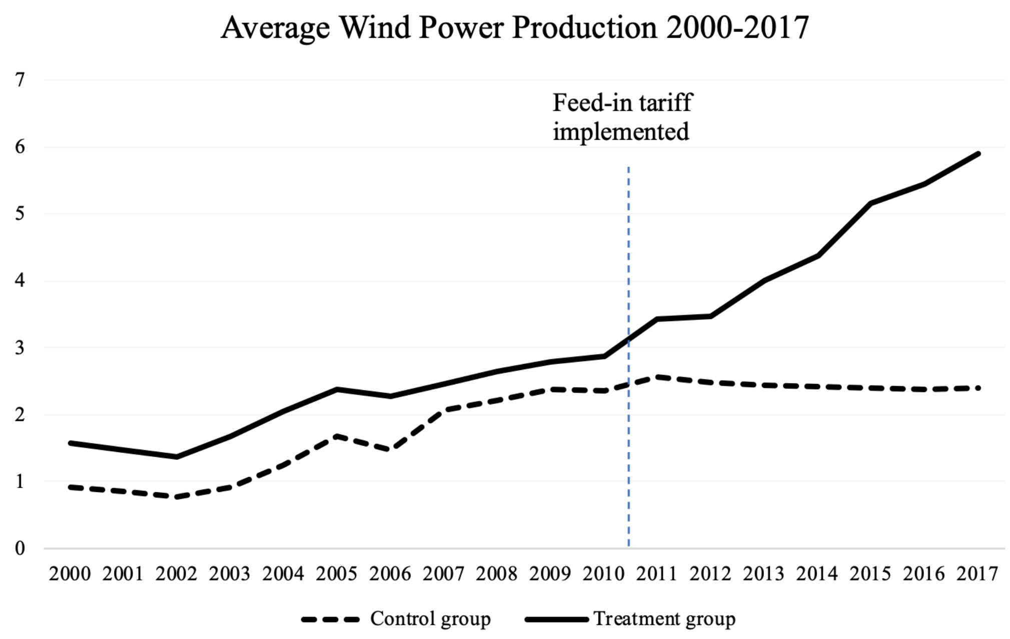

Figure 3*. Average wind power production between the years 2000-2017, expressed on a logarithmic scale (base 10). Source: Finnish Energy & VTT.*

Figure 3 employs a logarithmic scale instead of using the absolute wind power production amounts in GWh in order to communicate the rate of change in the amount of wind power generation. The rate of change for the control group's average wind power production slightly decreases in 2011 and then remains stable until 2017, while the rate of change in the treatment group's average wind power production is close to a linear growth. A linear increase on a logarithmic scale implies a constant growth rate (Robbins, 2012), which suggests that the treatment group's average wind power production grew at a nearly constant rate after the implementation of the feed-in tariff. The observed difference in the average wind power production growth between the control and treatment groups implicates that the feed-in tariff was plausibly effective in promoting wind power production in Finland.

4.5 Models

As aforementioned, the analysis on the effectiveness of the feed-in tariff in promoting wind power deployment is primarily based on a difference-in-difference estimation. Before that, however, it is studied what are the factors that are associated with the probability that a region receives the feed-in tariff funding on its wind power plants. This analysis is done using probit and logit approaches, which employ a region's feed in tariff status as the binary dependent variable. The probit and logit models are presented below. Two different models are used to analyze what variables are associated with the probability that a region's wind power plants receive the feed-in tariff in a given year.

(1) Probit

$$\Pr(\text{FIT}_{it} = 1 | GDP_{it}, plants_{it}, fossil_t, elprice_t, u_{it}) = \Phi(\beta_0 + \beta_1 GDP_{it} + \beta_2 plants_{it} + \beta_3 fossilFI_t + \beta_4 elprice_t + u_{it})$$

(1) Logit

$$\Pr(\text{FIT}_{it} = 1 | GDP_{it}, plants_{it}, fossil_t, elprice_t, u_{it}) = F(\beta_0 + \beta_1 GDP_{it} + \beta_2 plants_{it} + \beta_3 fossilFI_t + \beta_4 elprice_t + u_{it})$$

The dependent variable is denoted FIT_{it} and it represents the feed-in tariff status of region i in year t. If at least one wind power plant in region *i* received the feed-in tariff in year *t*, the variable FIT_{it} is equal to 1, and 0 otherwise. In Model 1, the dependent variables are annual regional GDP growth, GDP_{it}, number of wind power plants in a region, $plants_{it}$, national electricity production using fossil fuel resources and peat in year *t*, $fossilFI_t$, annual average electricity price in the country, $elprice_t$, and the error term, denoted as u_{it}.

Model 2 is similar to Model 1, but includes a variable representing proximity to coast, $coast_i$, and excludes the variable $plants_{it}$. These two variables are highly correlated with each other (covariance 0.52), which is why including them in the same model could create a case of multicollinearity. In the case of multicollinearity, changing the value of an explanatory variable affects the value of another explanatory variable, which is problematic for the estimates and any inference made on the results (Frost, 2019). Multicollinearity can create issues on how well the model fits the data but also affects the precision of the estimates negatively, weakening the statistical power of the estimated model (Frost, 2019). The association between a region's coastal proximity and feed-in tariffs is interesting based on Figure 2, which is why it was chosen to be included in a separate model. The probit and logit approaches to Model 2 are presented below.

(2) Probit

$$\Pr(\text{FIT}_{it} = 1 | GDP_{it}, fossil_t, elprice_t, coast_i, u_{it}) = \Phi(\beta_0 + \beta_1 GDP_{it} + \beta_2 fossilFI_t + \beta_3 elprice_t + \beta_4 coast_i + u_{it})$$

(2) Logit

$$\Pr(\text{FIT}_{it} = 1 | GDP_{it}, fossil_t, elprice_t, coast_i, u_{it}) = F(\beta_0 + \beta_1 GDP_{it} + \beta_2 fossilFI_t + \beta_3 elprice_t + \beta_4 coast_i + u_{it})$$

After analyzing what variables are associated with the probability of a region obtaining the feed-in tariff subsidy, the analysis moves on to the actual effect that the feed-in tariff has on the amount of wind power a region produces. This analysis is performed using panel data methods and difference-in-difference estimators. The panel data methods are included to get a general overview of the variables that are associated with higher levels of wind power production, while the difference-in-difference analysis focuses on the differences in wind power production between the treatment and control groups and the effect that the feed-in tariff has had on the treatment group's wind power production. Model 3 is analyzed as a general panel data model for two different time periods. The first time period covers the entire dataset from 2000 until 2017 and the second dataset covers a shorter period from 2007 until 2017. The reason for including two different length datasets is to see if the obtained coefficient estimates significantly change as a result of alteration to the data. From 2000 until 2007, the amount of wind power production fluctuated but remained quite low, while after 2007 a slight upward trend can be observed (see Figure 3). The period between 2007 and 2017 displays stronger growth throughout the time-period compared to 2000-2017, which is why it is interesting to see how the model reacts to changes in the time period. If no significant changes between the estimations are discovered, there is evidence of the model fitting to the data quite well, without being highly sensitive to changes in the data.

(3) Panel data – Basic model

$$power_{it} = \beta_0 + \beta_1 coast_i + \beta_2 hydro_{it} + \beta_3 elconsFI_t + \beta_4 fossilFI_t + \beta_5 nuclear_{it} + \beta_6 GDP_{it} + \beta_7 \boldsymbol{T}_t + \varepsilon_{it}$$

The dependent variable in the panel data model and the difference-in-difference models is the nominal wind power in a region during a given year, denoted $power_{it}$. Some explanatory variables are the same as in the probit and logit models: $coast_i$, $fossilFI_t$ and GDP_{it}. Additional explanatory variables are regional hydro power production, denoted $hydro_{it}$, the change in annual national electricity consumption, denoted $elconsFI_t$, regional nuclear power production, denoted $nuclear_{it}$, time controls as a vector of yearly dummy variables, denoted $\boldsymbol{T}_t$, and lastly, the error term ε_{it}.

When it comes to the main part of the study, the association between the feed-in tariff and the amount of wind power production in a region, the difference-in-difference method provides an excellent way to separate the effect from other variables. As aforementioned in Section 4.4, the difference-in-difference analysis typically compares two points in time: the pre-treatment period and the post-treatment period. Now, as the dataset in this study only covers years until the end of 2017, when the feed-in tariff was discontinued for new projects, one must employ year 2017 as the post-treatment time period. More ideal would have been to use data from years 2018 or 2019 as the post-treatment period, but due to data limitations it is not possible. All of the wind power projects and the nominal power of the new wind power plants receiving the feed-in tariff was known by the end of 2017, meaning that the dataset mainly covers all relevant data.

In order to perform a more traditional difference-in-difference analysis at first, only two years are included in the estimation: 2010 and 2017. These years were chosen to represent the pre- and post-treatment years and will hopefully present a clear difference of the feed-in tariff's effect in the results. When including only these two years in the analysis, the number of observations is only 38, possibly creating issues in the estimations, such as low statistical power. Therefore, the analysis also includes the whole panel data set from 2000 until 2017, and the results will be compared to the case of only the two years. A shorter dataset covering years 2007-2017 will be estimated for the difference-in-difference models as well. The reason is to obtain a view of the models' sensitivity to changes in the data.

(4) Difference-in-difference – Basic Model

$$power_{it} = \beta_0 + \beta_1 treatment_i + \beta_2 treatment_i * Y2017 + \beta_3 Y2017 + \varepsilon_{it}$$

Model 4 is a base version of the difference-in-difference model and only includes the necessary variables to find out the difference-in-difference effect. The dependent variable remains the same $power_{it}$, and the explanatory variables are a dummy variable representing the treatment group, denoted $treatment_i$ and a dummy variable representing year 2017, which represents the post-treatment year in the dataset of only years 2010 and 2017. The treatment group dummy variable takes care of the inherent differences between the treatment and control groups, while the year dummy accounts for the time trend the data experiences when moving from 2010 to 2017. Lastly, the main variable of interest is the interaction term of the treatment dummy variable and the dummy variable representing year 2017, denoted $treatment_i * Y2017$. The interaction term isolates the treatment effect and is the variable of interest in the analysis of the effectiveness of the feed-in-tariff.

(5) Difference-in-difference – Basic Model with additional regressors

$$power_{it} = \beta_0 + \beta_1 coast_i + \beta_2 hydro_{it} + \beta_3 treatment_i + \beta_4 treatment_i * Y2017 + \beta_5 Y2017 + \varepsilon_{it}$$

Model 5 includes two additional explanatory variables that are assumed to have a strong association with the variation in the dependent variable: $coast_i$ and $hydro_{it}$. This model is also estimated only for years 2010 and 2017, therefore providing only preliminary level results for the difference-in-difference analysis.

(6) Difference-in-difference – Main Model

$$power_{it} = \beta_0 + \beta_1 coast_i + \beta_2 hydro_{it} + \beta_3 treatment_i + \beta_4 treatment_i * startyear_{it} + \beta_5 \boldsymbol{T}_t + \varepsilon_{it}$$

Model 6 is similar to Model 5 in terms of variables, but it also includes vector $\boldsymbol{T}_i$ to control for the years.

(7) Difference-in-difference – Main Model with additional regressors

$$power_{it} = \beta_0 + \beta_1 coast_i + \beta_2 hydro_{it} + \beta_3 treatment_i + \beta_4 treatment_i * startyear_{it} + \beta_5 netimportsFI_t + \beta_6 GDP_{it} + \beta_7 \boldsymbol{T}_t + \varepsilon_{it}$$

Model 7 includes the most explanatory variables, adding annual domestic net imports, denoted $netimportsFI_t$, and regional GDP growth, denoted GDP_{it}, to the model.

5. Results

5.1 Probit and Logit models

All probit and logit specifications for models 1 and 2 imply that GDP growth is positively associated with the probability that wind power plants in a region obtain the feed-in tariff (see Table 3). The estimates for GDP are mostly significant on the 5 percent level across the probit and logit specifications. The size of this association cannot be stated based on the coefficient estimates directly due to the nonlinearity of the models, so the average marginal effects on the probability that a region's wind power plants obtain the feed-in tariff were calculated separately. For random effects logit of Model 1, a 1 percent increase in regional GDP is associated on average with a 0.66 percentage points increase on the probability that a region's wind power plants receive the feed-in tariff. These average marginal effects vary between 0.65 and 0.79

percentage points for Model 1 and between 0.90 and 0.94 percentage points for Model 2. When it comes to the fixed-effects logit model, an issue was encountered: because the feed-in tariff status does not change throughout the sample period for the five regions that do not receive it, all observations for those five regions are omitted by the fixed-effects estimation. This leaves only those regions in the estimated dataset whose wind power plants receive the feed-in tariff at some point during the sample period. This could cause issues in the estimated results. Therefore, the results obtained from the fixed effects logit models are merely used to add to the robustness of the estimates, and not used as the primary source of results in the binary model analysis. However, in this case the fixed effect logit results are also positive and significant, supporting the robustness of the results obtained from the random-effects and population-average logit and probit models (see Appendix 2, Table A5).

Table 3. Logit and Probit results.

	Model 1	Model 1	Model 1	Model 1	Model 2	Model 2	Model 2	Model 2
	RE logit	PA logit	RE probit	PA probit	RE logit	PA logit	RE probit	PA probit
Variables	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}
GDP_{it}	0.465*	0.155**	0.255**	0.094***	0.366**	0.152***	0.203***	0.084**
	(0.242)	(0.064)	(0.127)	(0.033)	(0.145)	(0.0762)	(0.079)	(0.039)
$plants_{it}$	1.557	0.354***	0.864	0.201***	-	-	-	-
	(1.665)	(0.103)	(0.793)	(0.0532)				
$fossilFI_t$	-0.001***	-0.001***	-0.001	-0.000***	-0.001***	-0.001***	-0.001***	-0.000***
	(0.0004)	(0.0000)	(0.0002)	(0.0000)	(0.0003)	(0.0001)	(0.0001)	(0.0001)
$elprice_t$	0.183***	0.0889***	0.103***	0.0418***	0.255***	0.108***	0.139***	0.0591***
	(0.0608)	(0.0176)	(0.031)	(0.0079)	(0.0878)	(0.0204)	(0.0475)	(0.0107)
$coast_i$	-	-	-	-	6.649**	2.634**	3.679**	1.460**
					(2.758)	(1.193)	(1.450)	(0.592)
Constant	6.404	3.095**	3.575	1.725**	6.445***	2.717**	3.638***	1.585**
	(5.432)	(1.389)	(2.528)	(0.742)	(2.085)	(1.193)	(0.521)	(0.668)
Years	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017
Obs.	324	324	324	324	324	324	324	342
Regions	18	18	18	18	18	18	18	18

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Model 1 includes the variable $plants_{it}$, representing the number of plants in a region during a given year. The coefficient estimates for $plants_{it}$ are positive across the different specifications of Model 1, but only significant (on the 1 percent level) for the population-averaged logit and probit models. The average marginal effects are 1.69 percentage points and 1.72 percentage points for the logit and probit models, respectively. This implies that, on average, each additional wind power plant in a region is associated with 1.69 or 1.72 percentage point increase in the probability that the region's wind power receives the feed-in tariff. The association that national electricity production using fossil fuel has on regions' feed-in tariff status is represented by the variable $fossilFI_t$, and its coefficient estimates are negative and highly significant (on the 1 percent level) across models 1 and 2. The average marginal effect is very low, however, with the highest average marginal effect being -0.003 percentage points. Electricity price is also included in both models and the coefficient estimates are all positive and highly significant (on the 1 percent level) across the different logit and probit specifications. The average marginal effect of Model 1 estimations for electricity price is between 0.26 and 0.42 percentage points, while the average marginal effects are slightly higher for Model 2, ranging between 0.62 and 0.67 percentage points. Lastly, Model 2 includes a variable representing the coastal proximity of a region. The coefficient estimates for this variable are all positive and significant on the 5 percent level. The average marginal effect varies between 15.9 and 16.4 percentage points, implying that coastal proximity has an important positive relationship with the probability that a region obtains the feed-in tariff for its wind power plants.

5.2 Panel data and difference-in-difference models

Before estimating the difference-in difference models, a basic panel data analysis was performed by estimating Model 3. As aforementioned, the Breusch-Pagan Lagrange multiplier and the Hausman tests suggested that the random-effects model is the most suitable one, but due to the assumption of zero correlation between the unobserved and observed characteristics in the random effects approach, the results shall be analyzed using the fixed effects and pooled OLS models as well. The panel data results are shown on Table 4. First, as could be expected based on the descriptive statistics, the coefficient estimates for the variable $cost_i$ are highly significant on the 5 percent level and positive throughout the different specifications. The variable has been omitted from the fixed effects model due to time invariance. The coefficient estimates of the pooled OLS and random effects specifications are similar in magnitude and imply that a region's coastal proximity is, on average, associated with 22.30 or 20.30 GWh higher nominal wind power compared to regions that are not located near to a coast.

Table 4. Panel data model results.

	Model 3 OLS	Model 3 FE	Model 3 RE	Model 3 OLS	Model 3 FE	Model 3 RE
Variables	$power_{it}$	$power_{it}$	$power_{it}$	$power_{it}$	$power_{it}$	$power_{it}$
$coast_i$	22.30***	-	20.30**	35.05***	-	34.35**
	(5.518)		(8.427)	(8.858)		(13.85)
$hydro_{it}$	0.0193***	0.0617**	0.0227**	0.0277***	0.0573**	0.0292**
	(0.0045)	(0.0220)	(0.0091)	(0.0062)	(0.0203)	(0.0115)
$elconsFI_t$	1.264	1.089	1.275	1.319	1.226	1.372
	(2.879)	(1.131)	(1.111)	(3.658)	(1.184)	(1.168)
$fossilFI_t$	-0.00054	-0.00035	0.00013	-0.0054**	-0.0051**	-0.0054**
	(0.0030)	(0.0014)	(0.0011)	(0.0022)	(0.0024)	(0.0025)
$nuclear_{it}$	0.00112	-0.0410***	0.0013	0.0015	-0.0746**	0.0015
	(0.0007)	(0.0057)	(0.0009)	(0.0011)	(0.0133)	(0.0015)
GDP_{it}	0.678	1.229**	0.886**	1.401	2.257**	1.844**
	(1.179)	(0.515)	(0.440)	(2.089)	(1.003)	(0.928)
Constant	-15.10	10.98	-32.10	128.1*	204.5***	125.9**
	(69.51)	(47.45)	(36.13)	(66.57)	(39.87)	(60.23)
Years	2000-2017	2000-2017	2000-2017	2007-2017	2007-2017	2007-2017
Time effects	yes	yes	yes	yes	yes	yes
Observations	324	324	324	209	209	209
# Regions	19	19	19	19	19	19
Adj. R^2	0.261	0.203	0.307	0.297	0.181	0.347

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

When the sample period is shortened to only cover the years 2007-2017, the coefficient estimates for coastal proximity increase, but the magnitudes between the pooled OLS and the random effects model are still close to each other. The increase in the coefficient estimates is plausibly due to the fact that, as the time period is shorter, the average nominal wind power per region is higher since it does not need to be averaged over such a long period as when the data set covers the years 2000-2017. Another variable, whose coefficient estimates are highly significant (mainly on the 5 percent level) and positive across the different specifications, is regional hydro power production. Again, the magnitudes between the different models are quite similar. To interpret the coefficient estimate for $hydro_{it}$, 1 GWh increase in hydro power production in a region is, on average, associated with 0.0193 GWh increase in nominal wind power in the same region. This relationship is quite low, but it still suggests that there is a positive relationship between the production of the two renewable power sources. Changes in national electricity consumption do not seem to have a relationship with wind power production as the coefficient estimates remain insignificant throughout the different model specifications and the two versions of the dataset.

Table 5. Difference-in-difference results Models 4 and 5.

	Model 4 OLS	Model 4 FE	Model 4 RE	Model 5 OLS	Model 5 FE	Model 5 RE
Variables	$power_{it}$	$power_{it}$	$power_{it}$	$power_{it}$	$power_{it}$	$power_{it}$
$treatment_i$	6.242	-	6.242	-43.42	-	-43.42
	(6.511)		(6.601)	(27.34)		(28.25)
$treatment_i * startyear_{it}$	143.3**	143.3**	143.3**	140.2**	121.3**	140.2**
	(66.15)	(62.67)	(63.58)	(59.10)	(49.85)	(63.19)
$coast_i$	-	-	-	62.95**	-	62.95**
				(27.99)		(24.61)
$hydro_{it}$	-	-	-	0.0454*	0.322	0.0454
				(0.027)	(0.226)	(0.029)
Constant	5.406	9.677	5.406	-24.20	-206.3	-24.20*
	(3.560)	(21.44)	(3.609)	(15.44)	(166.4)	(14.51)
Years	2010 and 2017	2010 and 2017	2010 and 2017	2010 and 2017	2010 and 2017	2010 and 2017
Time effects	yes	yes	yes	yes	yes	yes
Observations	38	38	38	38	38	39
# Regions	19	19	19	19	19	19
Adj. R^2	0.149	0.271	0.218	0.319	0.366	0.410

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

After the panel data model (Model 3), the difference-in-difference models (Models 4-7) were estimated. The results of models 4 and 5 are presented in Table 5. In Model 4, only the treatment effect ($treatment_i * startyear_{it}$), which is the variable of interest for the main analysis, is significant on the 5 percent level. The coefficient estimate for the treatment effect is quite high and all three specifications estimate the same coefficient of 143.3. The similarity in the results is plausibly due to the low number of observations used to estimate these models. Model 5 includes coastal proximity and regional hydro power production as regressors. As in other results presented thus far, the coefficient for coastal proximity is highly significant (on the 5 percent level) and positive across the specifications. Hydro power, on the other hand, is only weakly significant (on the 10 percent level) for the pooled OLS specification and has a low positive association with the average region's nominal wind power. In Model 5, the coefficient for the treatment effect is slightly lower for all specifications, but still highly significant on the 5 percent level. These results present the very basic version of the difference-in-difference effect, and due to the low number of observations one should be cautions not to build the analysis around these coefficient estimates. These estimates do, however, give the basic idea that the treatment effect is positive and significant, but Models 6 and 7 should present more trustworthy results, as they include the entire dataset between the years 2000 and 2017, and therefore, many more observations and a higher statistical power.

Table 6. Difference-in-difference results Models 6 and 7.

	Model 6 OLS	Model 6 FE	Model 6 RE	Model 7 OLS	Model 7 FE	Model 7 RE
Variables	$power_{it}$	$power_{it}$	$power_{it}$	$power_{it}$	$power_{it}$	$power_{it}$
$treatment_i$	-8.137***	-	-10.12**	-8.566***	-	-10.59*
	(2.377)		(5.574)	(2.410)		(5.775)
$treatment_i * startyear_{it}$	61.53***	59.08**	61.76***	63.38***	60.47**	63.37***
	(12.63)	(21.70)	(63.58)	(12.84)	(21.50)	(23.04)
$coast_i$	19.46***	-	18.35**	19.38***	-	18.34**
	(4.249)		(7.225)	(4.303)		(7.388)
$hydro_{it}$	0.0163***	0.0522**	0.0195**	0.00162***	0.0536**	0.0193**
	(0.0042)	(0.0198)	(0.0083)	(0.00414)	(0.0204)	(0.00837)
$netimportsFI_t$	-	-	-	0.00463	0.0053*	0.00471**
				(0.00375)	(0.00192)	(0.00185)
GDP_{it}	-	-	-	0.206	0.667	0.401
				(1.071)	(0.413)	(0.310)
Constant	-14.22**	-34.24*	-14.46**	-68.97	-98.32	-70.33*
	(6.049)	(19.36)	(7.011)	(45.58)	(40.59)	(26.64)
Years	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017	2000-2017
Time effects	yes	yes	yes	yes	yes	yes
Observations	342	342	342	342	342	342
# Regions	19	19	19	19	19	19
Adj. R^2	0.309	0.257	0.350	0.307	0.256	0.352

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The results for Models 6 and 7 are presented in table 6. By including more variables compared to Model 5, Model 6 estimates coefficients that are more significant than in Model 5. The treatment effect $treatment_i * startyear_{it}$ is now lower, but the high level of association with regional nominal wind power is clear. The coefficient for $treatment_i * startyear_{it}$ gives the treatment effect for the treatment group, while adding the coefficient for $treatment_i$ to it, one obtains the estimated mean difference between treatment and control groups. Taking the pooled OLS estimates for model 6, for example, the treatment effect is 61.53, implying that the treatment effect of the feed-in tariff for the treatment group regions is on average 61.53 GWh higher nominal wind power. The estimated mean difference between treatment and control groups, on the other hand, is 53.49. This means, that after the feed-in tariff was implemented, the treatment groups receiving the tariff had, on average, 53.39 GWh higher nominal wind power than the control group regions. Model 7 includes domestic net electricity imports and regional GDP growth as additional regressors. The results for the coefficient estimates for the treatment effect, coastal proximity, and hydro power production remain quite similar as in the previous model, while net electricity imports are only weakly positive and significant for the fixed effect and random effect specifications, and regional GDP growth is not significant in any of the three specifications.

5.3 Sensitivity Analysis and Robustness Checks

In addition to the main dataset covering the period 2000-2017, a shorter dataset covering only the period 2007-2017 was used as a sensitivity analysis for the obtained results. Tables A5-A7 in Appendix 2 provide the results for the probit and logit models as well as for the difference-in-difference models when using the shorter dataset. Overall, the estimated results using the shorter dataset are very similar to the results obtained using the full dataset across all models, implying that they do not seem to be sensitive to changes in the dataset. Additionally, changing the variables between the models (e.g. differences in variables in Models 6 and 7) does not seem to affect the obtained results significantly, indicating that the models perform quite well in explaining the variation in the dependent variables. When it comes to the fit of the models, the adjusted R-squared values are provided for Models 3-7. The adjusted R-squared values are not particularly high, but estimations that are able to explain between 30 and 40 percent of the variation in the amount of nominal wind power are already providing significant information. Furthermore, since some key factors affecting the amount of nominal wind power, such as technological progress, could not be included in the models, the obtained level of adjusted R-squared can be considered to be satisfactory.

Assessing the robustness of the results obtained from the logit and probit models is done using the percentage correctly predicted values, calculated using the average random intercept that has been averaged over the observations. For Model 1, the sensitivity of the predicted probabilities varies between 81.63 and 85.71 percent and the specificity varies between 94.55 and 95.26 percent across the random-effects and population-averaged logit and probit specifications. Sensitivity refers to correct classification of true positives and specificity to the correct classification of true negatives. High values of sensitivity and specificity imply that the estimations have provided more correct predictions and that the rate of false negative and false positive predictions is low. For Model 4, the specificity across models is similar to that of Model 1, but the sensitivity is somewhat lower at around 76 percent. For the shorter dataset covering the period 2007-2017, the obtained sensitivity and specificity are both above 80 percent for all random effects and population-averaged logit and probit models. Lastly, it was tested if including Åland in the dataset that was used to estimate the probit and logit models would affect the results in an attempt to analyze the results' robustness. It was found that there were hardly any differences between the estimations that included or did not included Åland in the dataset. This provides further confidence in the obtained results.

6. Analysis and Conclusion

The estimated regressions mainly show the expected results. The main results can be summarized as follows: The feed-in tariff shows a large positive relationship to the nominal wind power in a region. This relationship is what this study aimed to analyze and it provides the expected answer to the research question. The exact magnitude of the positive relationship is difficult to determine, but an average estimate provided by Models 6 and 7 implies that regions where wind power was eligible to receive the feed-in tariff had approximately 50 GWh higher average wind power production than regions where wind power was not eligible to receive the feed-in tariff. Another important factor contributing to the amount of wind power in a region is the region's location. Coastal proximity is highly positively associated with the amount of nominal wind power across the different models that have been estimated. Not only that, but coastal proximity is also positively associated with the probability that a region's wind power plants receive the feed-in tariff. Higher GDP growth in a region is also positively associated with the probability of obtaining the feed-in tariff but results on its relationship with nominal wind power in a region are not as straightforward as some models do not find a significant positive relationship but others do. Hydro power production in a region is positively associated with wind power production, which could be due to the region's preferable conditions for renewable energy production, some other factors that make renewable energy production attractive in the region, or there might not exist a real reason for the observed relationship, as the results were quite low in magnitude.

The treatment effect of the feed-in tariff is highly positive across the different models, and similar results were obtained when estimating the models with different sample periods. Based on the sensitivity analysis and robustness checks, the results seem trustworthy and sensible. Therefore, the conclusion can be made that the feed-in tariff was an effective way to increase investment in wind power, and hence, the wind power capacity of Finland. This result is in line with findings by Ertürk (2012) and Butler and Neuhoff (2008), for example. As stated in Section 3.2, there is no univocal opinion on the effectiveness of the feed-in tariff, and results depend strongly on the individual characteristics of each country's energy policy. As aforementioned, it is clear that some of the observed increase in the nominal wind power can be attributed to technological advancement in wind power turbines but measuring the technological advancement and including it in the regression analysis is very challenging. According to Kyytsönen (2018), technology development in the Finnish wind power industry has been particularly fast, significantly lowering the production costs. The fast technological development enabled the first Scandinavian wind power projects that are profitable without government support to be developed in Finland in 2018 (Kyytsönen, 2018; Alkio, 2018). The high level of the Finnish feed-in tariff might have been one of the reasons that boosted technological development as wind power producers have likely wanted to maximize the additional profits to be obtained from the tariff payments. If this is the case, then the Finnish feed-in tariff scheme could be claimed to have been very effective, as not only was the amount of wind power significantly increased, but it also contributed to technological development in such a large extent, that Finland was one of the first countries to make wind power profitable without subsidies. This implies that the need for government support should not be as crucial to further increase wind power capacity in the future, and that wind power could attract investments on its own. Financial institutions consider investments in Finnish wind power to be low risk, therefore boosting the investment possibilities in the coming years (Laatikainen, 2018). When it comes to the cost-effectiveness of the Finnish feed-in tariff scheme, the policy has not been considered to be as successful. As mentioned, the cost to the government will be measured in several billions of euros by the year 2030. This is in line with the results by Frondel et al. (2010), who found that the feed-in tariff, or other renewable energy policies, have not been a cost-effective means of climate protection.

Naturally, it would also have been interesting to study the time period after 2017 and to see how Finnish wind power production has continued evolving after the tariff scheme was ended for new wind power projects. The positive trend in the country's wind power production seen in Figure 3 would suggest a continued increase even after governmental support for new wind power projects was discontinued. Another way this study could be extended further, would be to compare the development of Finnish wind power to countries with other similar characteristics, such as Sweden, or to other countries where wind power production is still only gaining status as a significant energy source. In 2034, after the last feed-in tariff payments are made to the wind power producers, accurate analysis on the cost-effectiveness of the tariff scheme can be performed. Due to the fluctuating electricity prices, the amount of tariff payments to producers is difficult to estimate precisely. The amount of electricity produced from wind power is not constant either, further complicating the estimation of the total cost of the tariff scheme.

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Appendix 1 – Additional graphs and tables for Descriptive Statistics

Table A1. Average regional GDP growth 2000 - 2017

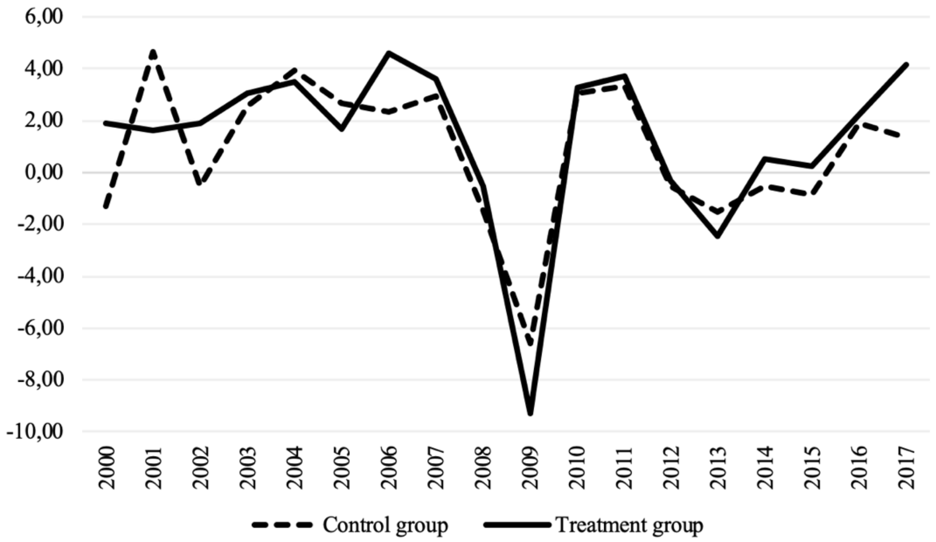

Table A2. Covariance matrix.

	Nominal wind power	FIT	Coastal proximity	Plants	Regional GDP growth	Hydro power	Nuclear power	Fossil electricity	Electricity consumption	Electricity price	Net electricity imports
Nominal wind power	1.00										
FIT	0.49	1.00									
Coastal proximity	0.24	0.19	1.00								
Plants	0.79	0.51	0.52	1.00							
Regional GDP growth	0.06	0.05	-0.02	0.00	1.00						
Hydro power	0.36	0.24	0.21	0.45	0.05	1.00					
Nuclear power	0.07	0.08	0.31	0.20	-0.05	-0.10	1.00				
Fossil electricity	-0.29	-0.53	0.00	-0.27	0.20	-0.06	-0.00	1.00			
Electricity consumption	-0.01	-0.08	0.00	0.01	0.32	0.01	0.00	0.38	1.00		
Electricity price	-0.02	-0.02	0.00	0.05	0.00	0.00	0.00	0.14	0.55	1.00	
Net electricity imports	0.27	0.46	0.00	0.25	-0.12	0.04	0.00	-0.90	-0.13	0.00	1.00

Table A3.

Breusch-Pagan Lagrange Multiplier test for random effects.

	Var	sd = sqrt(Var)
power	5282.976	72.684
e	3656.105	60.466
u	471.9028	21.723

H0: Pooled OLS appropriate, H1: Random effects appropriate

Test: Var(u) = 0

Chibar2(01) = 16.76

Prob > chibar2 = 0.000

Reject the null hypothesis and conclude that random effects model is more appropriate than pooled OLS model.

A4.

Hausman test for fixed versus random effects

H0: Random effects model is appropriate

H1: Fixed effects model is appropriate

Output:

Chi2(5) = 5.13

Prob > chi2 = 0.4006

Do not reject the null hypothesis and conclude that random effects model is more appropriate than fixed effects model.

Appendix 2 – Additional Results

Table A5. Results for fixed-effects logit and probit models.

	Model 1	Model 1	Model 2	Model 2
	FE logit	FE logit	FE logit	FE logit
Variables	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}
GDP_{it}	0.399**	0.207	0.399**	0.207
	(0.183)	(0.213)	(0.183)	(0.213)
$plants_{it}$	-	-	-	-
$fossilFI_{t}$	-0.00135***	-0.00180***	-0.00135***	-0.00180*
	(0.00041)	(0.00095)	(0.00041)	(0.00095)
$elprice_{t}$	0.305*	0.643	0.305**	0.643
	(0.138)	(0.534)	(0.138)	(0.534)
$coast_{i}$	-	-	-	-
Constant	-	-	-	-
Years	2000-2017	2007-2017	2000-2017	2007-2017
Observations	234	77	234	77
# Regions	13	11	13	11

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A6. Results for logit and probit for years 2007-2017.

	Model 1	Model 1	Model 1	Model 1	Model 2	Model 2	Model 2	Model 2
	RE logit	PA logit	RE probit	PA probit	RE logit	PA logit	RE probit	PA probit
Variables	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}	FIT_{it}
GDP_{it}	0.498**	0.170***	0.272**	0.0994***	0.440***	0.171**	0.241***	0.0939***
	(0.220)	(0.0571)	(0.117)	(0.0308)	(0.165)	(0.0699)	(0.0871)	(0.0345)
$plants_{it}$	1.337*	0.363***	0.734*	0.208***	-	-	-	-
	(0.746)	(0.115)	(0.378)	(0.0578)				
$fossilFI_t$	-0.0010***	-0.0004***	-0.0006***	-0.0002***	-0.0009***	-0.0004***	-0.0005***	-0.0002***
	(0.00024)	(0.00007)	(0.00012)	(0.00004)	(0.00019)	(0.00007)	(0.00009)	(0.00004)
$elprice_t$	0.0126	0.0251	0.00915	0.0106	0.0344	0.0229	0.0196	0.0126
	(0.0665)	(0.0251)	(0.0369)	(0.0108)	(0.0617)	(0.0182)	(0.0339)	(0.00985)
$coast_i$	-	-	-	-	7.045**	2.888**	3.859**	1.600**
					(3.107)	(1.254)	(1.613)	(0.660)
Constant	9.279**	3.825**	5.162***	2.128***	9.452***	3.554***	5.253***	2.045***
	(3.633)	(1.522)	(1.899)	(0.814)	(2.312)	(1.363)	(1.262)	(0.747)
Years	2007-2017	2007-2017	2007-2017	2007-2017	2007-2017	2007-2017	2007-2017	2007-2017
Observations	198	198	198	198	198	198	198	198
# Regions	18	18	18	18	18	18	18	18

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A7. Results for Models 6 and 7 for years 2007-2017.

	Model 6 OLS	Model 6 FE	Model 6 RE	Model 7 OLS	Model 7 FE	Model 7 RE
Variables	power_{it}	power_{it}	power_{it}	power_{it}	power_{it}	power_{it}
$\mathrm{treatment}_{i}$	-7.899**	-	-9.111	-8.474**	-	-9.408
	(3.921)		(7.485)	(3.946)		(7.651)
$\mathrm{treatment}_{i} * \mathrm{startyear}_{it}$	47.38***	46.33**	46.84**	48.42***	46.32**	47.26***
	(11.27)	(17.74)	(18.23)	(12.36)	(17.55)	(17.98)
coast_{i}	30.88***	-	30.18***	31.02***	-	30.73***
	(7.089)		(11.18)	(7.275)		(11.60)
hydro_{it}	0.0242***	0.0515**	0.0263**	0.0240***	0.0540**	0.0257**
	(0.00607)	(0.0215)	(0.0111)	(0.00606)	(0.0219)	(0.0110)
$\mathrm{netimportsFI}_{t}$	-	-	-	0.00382	0.00439**	0.00382**
				(0.00401)	(0.00171)	(0.00157)
GDP_{it}	-	-	-	0.676	1.498*	1.133
				(2.042)	(0.852)	(0.734)
Constant	-23.25**	-32.50	-23.61*	-73.12	-94.54**	-75.06**
	(9.206)	(23.51)	(12.05)	(52.95)	(44.73)	(29.48)
Years	2007-2017	2007-2017	2007-2017	2007-2017	2007-2017	2007-2017
Time effects	yes	yes	Yes	yes	yes	Yes
Observations	209	209	209	209	209	209
# Regions	19	19	19	19	19	19
Adj. R^2	0.322	0.252	0.367	0.316	0.204	0.368

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1