WISEflow
Europe/Oslo(CEST)
30 Jun 2024

Handelshøyskolen BI

GRA 19703 Master Thesis

Final Thesis Master of Science W 100%

Predefinert informasjon

Startdato:	08-01-2024 09:00 CET
Sluttdato:	01-07-2024 12:00 CEST
Eksamensform:	T
Termin:	202410
Vurderingsform:	Norsk 6-trinns skala (A-F)
Flowkode:	202410||11436||IN00||W||T
External assessor:	External assessor 1
Internal assessor:	Internal assessor 1

Navn:

Anders Reime, Mikkel Myrmel Bakke

Informasjon fra deltaker

Tittel *:	Understanding the Regional Dynamics of Solar Energy Adoption: A Case Study of Norway's Electricity Market
Navn på veileder *:	Karin Kinnerud

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

G r u p p e

Gruppenavn:	(Anonymisert)
Gruppenummer:	294
Andre medlemmer i gruppen:	

Understanding the Regional Dynamics of Solar Energy Adoption: A Case Study of Norway's Electricity Market

MSc in Business, major in Economics

BAKKE M., MIKKEL & REIME, ANDERS

"Do regional price differences for electricity affect PV investments in Norway?"

Supervisor: Karin Kinnerud

Abstract

This thesis investigates the impact of bidding zones on solar photovoltaic (PV) uptake in Norway by replicating and adapting the Synthetic Control Method (SCM) used in a similar study conducted in Sweden. The SCM, developed by Abadie and Gardeazabal (2003) and further improved by Abadie, Diamond, and Hainmueller (2010), constructs a synthetic control unit by assigning optimized weights to a combination of control units, creating a counterfactual that closely resembles the treated unit before the intervention. This method addresses the biases inherent in simple before-and-after comparisons or difference-in-differences approaches. Drawing inspiration from the study "Do separate bidding zones within countries create imbalances in PV uptake? Evidence from Sweden" by Johanna Fink, this paper adapts the SCM to the Norwegian context by accounting for structural and socio-economic differences between the two countries.

The results demonstrate that while bidding zones and price divergence have a significant impact on PV uptake in Norway, the choice of control variables is crucial to the robustness of the synthetic control. Our findings highlight the importance of avoiding overfitting and ensuring that the model captures true underlying patterns rather than noise. This study contributes to the literature on renewable energy adoption and provides insights for policymakers on the effects of electricity market segmentation.

Acknowledgements

We would like to express our gratitude to Nord Pool for their electricity price data, which was important in contextualizing the economic aspects of our study. Our sincere thanks go to the Norwegian Water Resources and Energy Directorate (NVE) for providing datasets on solar installations in Norway and insights that were fundamental to our research. We are also grateful to STRÅNG at the Swedish Meteorological and Hydrological Institute for their meteorological data, which aided our analysis. STRÅNG data used here are from the Swedish Meteorological and Hydrological Institute (SMHI), and were produced with support from the Swedish Radiation Protection Authority and the Swedish Environmental Agency. Special thanks to our thesis supervisor, Karin Kinnerud, for her insightful feedback, constructive criticism, and encouragement throughout this journey. Your collective contributions have been instrumental in the successful completion of this thesis, and we are deeply grateful for your support. We acknowledge the use of StataSE 18 for the data analysis conducted in this study.

Contents

Table of Figures

Table of Tables

1.0 Introduction

Throughout human history, humans have relied on energy to assist and improve their lives. Since the discovery of fire, humans used it for heat and light while labor was done manually. Fire also enabled innovation, such as pots and bricks from clay (Pain, 2017). As we have evolved and developed as a species, we have continued to evolve and invent through our use of energy. Thus, our energy demands have grown larger, and we have had to find new ways to extract it. We know that there is a strong correlation between reliable access to energy and economic growth. This became very clear during the industrial revolution when Britain started using coal as fuel in their iron production, as cheap fuel allowed them to bypass the constraints of an organic economy. Since this, hydrocarbons have been the world's primary energy source (Wrigley, 2013).

While the exact numbers are debated, it is almost universally agreed that human activity is the main cause of global warming. We see a need to reduce our greenhouse gas emissions to mitigate the effects of this, and energy is by far the biggest contributor of climate change. According to the UN Development Programme, it accounts for 73% of human caused greenhouse gas emissions. They also state that as of 2017, only 17% of the world power was generated using renewable sources (*UNDP*, n.d.). Moving towards a net zero for emissions in 2050, as per the Paris Agreement, will require a substantial shift in how we produce and consume energy. This was a goal set to keep global warming to no more than 1,5°C (*Net Zero Coalition*, n.d.).

In 2022, the Norwegian Government was asked by Parliament to set a goal of 8 TWh in solar by 2030 (*Stortinget vedtak 923*, 2022). To reach this goal, major investments must be made into solar infrastructure. The Norwegian Water Resources and Energy Directorate's (NVE) latest outlook estimate a production level of 2.7 TWh from solar by 2028, further illustrating the gap between the government's goals and the current projections (*Fortsatt positiv kraftbalanse mot 2028 - NVE*, 2024). We want to look at what drives investment in solar photovoltaic (PV) in previous years, to help policy makers make informed decisions and help create policies that incentivizes the market to invest. Our hypothesis is that electricity prices is the main driver of investment up until now, along with innovation in the field driving costs down. By looking at price trends and use of solar while controlling for other factors such as population, income level and solar irradiation levels, we hope to get a usable analysis of what drives investment today.

There has been some research on the topic of solar power and PV in Norway already, but for now it has been limited. Most of it has focused on the barriers of developing the solution in Norway due to low energy prices. Thus, we believe that our research can contribute to the literature in this area, and we believe our findings may benefit many different stakeholders. With the recent divergence in electricity price across the different bidding zones (BZ), the situation has changed, and we believe this can be an exciting new field that needs to be explored.

Building upon the work of Fink (2023), this thesis explores the impact of BZ on solar PV uptake in Norway using the Synthetic Control Method (SCM). While Fink examined this phenomenon in Sweden, this study adapts the methodology to the Norwegian context, with modifications to the control variables to better suit regional characteristics and socio-economic factors. We will come back to the specific modifications and adaptations that were made to better fit the Norwegian context, and subsequently how our model differs from previous research. We have also chosen to use the difference-in-differences (DiD) method as a supplement to the SCM, to hopefully get a better understanding of the differences between municipalities in different BZ.

The incentives to invest in PV panels has been reviewed before from several different perspectives, which we will highlight in our literature review. We have not been able to find, for Norway, extensive research that looks at the importance of price variations since the full outbreak of the Russian-Ukrainian war which greatly elevated energy prices in Europe. Since the invasion of Ukraine by Russia in February 2022, Europe has experienced elevated prices on energy (European Council, 2024). The implications of this will be further reviewed in our literature review.

1.1 Research question

The primary objective of this thesis is to look at what is driving investment in solar energy through PVs in Norway, using the SCM to conduct a natural experiment on the border region where the high-tariff BZ NO1 and NO5 meet the low-tariff NO3. We believe this can help answer our research question *"Do regional price differences for electricity affect PV investments in Norway?"*.

1.2 Limitations

Our work focuses on the effects of price differences in electricity prices between BZ in Norway. We have tried to control for variables that we believe are relevant for investment in solar panels, but we acknowledge that there may be other contributing factors that drive PV uptake. For example, we have not focused on the decision-making process of buying solar panels, or how long the process is from decision-making to installation and connection to the grid. Our datasets are limited to installations that are connected to the grid. This was led by data availability, as there is currently no registry of installations that are not connected to the grid in Norway.

We have also not considered the temporary rise in unemployment for Norway during the recent Covid-19 pandemic. This may have had an impact on the outcome variable, but unemployment is relatively low during this period as well, so we chose to not include it. We have also not distinguished between types of installations, or ownership i.e. installations owned by private citizens, businesses, or public entities. Changes to the structure of BZ within our estimation period have not been taken into account, as we do not expect this to have had a major impact on prices (*Statnett Adjusts the Interface between the Central Norway and Western Norway Bidding Zones*, 2022)

2.0 Background

Norway has been utilizing electric power since 1877, initially for lighting, heating, and trams. Over time, coal, wood, and kerosene were gradually replaced by electric power. Today, oil and electricity are the primary energy sources used in Norway. Looking ahead, the Norwegian government plans to phase out all energy sources except for electricity from renewable resources (Valmot, 2018). We believe that solar PV can play a crucial role in this transition, not only for the global energy landscape but also for Norway.

PV panels have long been used in satellites, spacecraft, photographic equipment, lighthouses, and remote cabins and houses not connected to the grid. This was primarily due to high costs and the general lack of economic feasibility for solar panels, given Norway's cheap and reliable hydroelectric power (Hofstad et al., 2024). However, this changed when electricity prices skyrocketed, especially in southern Norway. Prices in bidding zones NO1, NO2, and NO5 rose significantly higher than in NO3 and NO4. This price disparity was largely due to the proximity to Europe and its high electricity prices, as well as the low transmission capacity between different BZ in Norway. (Holstad, 2023)

Norway has not always had five BZ. According to Statnett (2024), the power grid has been developed with five BZ because electricity is produced and consumed regionally. If Norway were to have only one BZ, the power grid would need significantly more expansion, which would be costly. Moreover, such extensive expansion is unnecessary since electricity is generated regionally. Since energy production in Norway largely depends on weather, this can lead to substantial variations in production between BZ. This can subsequently cause considerable differences in electricity prices across the various BZ. In contrast, countries like Poland and France, which rely on coal and nuclear power respectively, can regulate their electricity production more consistently. Norway, known for its many water reservoirs, has some ability to regulate production, but this capability has its limitations (*Executive Summary – France 2021 – Analysis*, n.d.) (*Coal-Fired Poland Goes Nuclear*, 2022) (*Derfor har vi prisområder for strøm i Norge*, 2024).

It was long believed that Norway was poorly suited for solar PV due to its lower sunlight irradiation levels compared to other countries and its cold, dark winters. This reduces the utility of solar energy when electricity demand is highest. However, with the significant drop in PV panel-prices in recent years, solar cells have proven to be economically viable in several cases. Also, stringent regulations from the EU now require new and existing buildings to be more energy-efficient and environmentally friendly. In so-called “green buildings”, which are designed to use as much energy as they generate, solar PV have become one of the primary solutions for energy generation (Hofstad, 2024).

With the EU's strict requirements, there is a strong likelihood that more large buildings will be equipped with PV panels in the coming years. Interestingly, the solar irradiance on optimally oriented surfaces in northern Norway is not much lower than in Central Europe, which is currently experiencing a surge in solar energy usage. This shows that Norway has considerable potential for solar energy adoption, despite earlier assumptions to the contrary according to Hofstad (2024).

Norway’s unique geography and its regional power grid offers a valuable opportunity to investigate how electricity prices influence investment in PV. In areas where electricity prices vary significantly over short distances, the impact of these price differences on solar adoption becomes more apparent. By drawing a boundary separating the bidding zones NO1 and NO5 in the south from NO3 in the north, we can compare PV uptake in municipalities located on either side of this line. This comparison allows us to observe how higher electricity prices in the southern zones, driven by their proximity to the European market and limited transmission capacity, encourage more PV installations.

Understanding this relationship can help policymakers design more effective strategies and incentives to promote renewable energy like PV, even in regions with less solar irradiance. By focusing on municipalities near the boundary, we can control for other factors and better isolate the effect of electricity prices on solar panel adoption. This was done by creating different border regions along the boundary between the low- and high-tariff bidding zones. The exact definitions of these border regions will be further explained in our data-section.

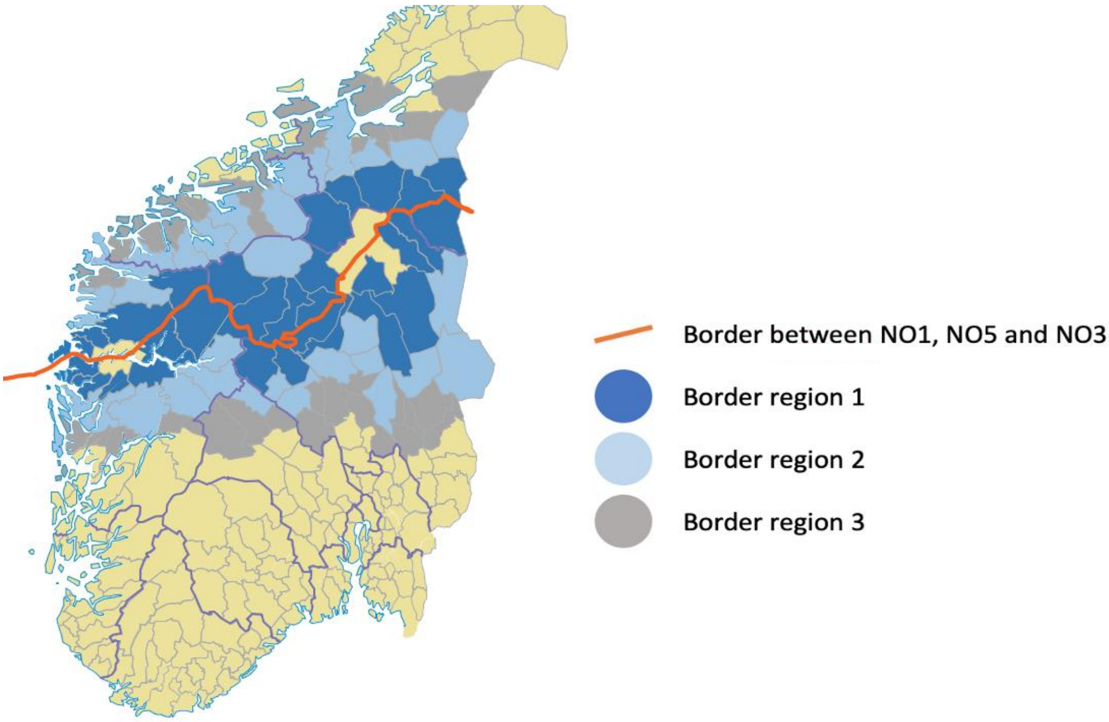

Figure 1: Showing the boundary between NO1 and NO5 in the high-tariff area and NO3 in the low-tariff area.

2.1 Incentives for PV

Investing in solar PV in Norway is encouraged through various economic and governmental incentives. Economic incentives, such as reduced electricity bills and the ability to sell excess power back to the grid, make solar panel systems financially attractive. The electricity generated by systems installed on rooftops is primarily used by the building on which they are located, with any excess power being fed back into the electricity grid. Currently, the system is designed in such a way where the consumer receives additional compensation for the electricity they generate in areas with a power deficit, while they receive slightly less compensation for the electricity that is sent back to the grid in areas with a power surplus (*Plusskunder*, 2023). By generating their own electricity, households and businesses can save substantial amounts on their electricity bills, and selling excess power can provide additional income. Another economic advantage is the increased property value. Properties equipped with solar panel are often seen as more desirable, potentially leading to increases in listing prices (Smith, 2023) (*Støtte Til Solceller*, n.d.).

Enova, a state enterprise that promotes and subsidizes environmentally friendly energy solutions, offers financial support to households installing solar panel systems. This support has evolved over time to meet market needs and technological advancements. As of October 2023, homeowners can receive up to NOK 32,500 in support from Enova, which includes a fixed rate of NOK 7,500 plus NOK 1,250 per installed kW, up to a maximum capacity of 20 kW (*Solcelleanlegg | Energitiltak | Solenergi*, 2022) (*Enova reduserer støtten til solceller 1. oktober 2023*, n.d.).

By providing financial incentives, Enova helps reduce the initial cost burden, making solar installations more accessible to a broader range of homeowners. This support not only encourages the use of renewable energy but also contributes to Norway's overall environmental goals by reducing reliance on fossil fuels and lowering greenhouse gas emissions. The support for solar panel systems has been particularly popular in recent years. Their impact is evident in the increasing number of households adopting solar energy solutions, driven by the financial support and the growing awareness of the environmental benefits of renewable energy. By continuously adapting its support programs to align with technological advancements and market trends, Enova ensures that its initiatives remain effective and relevant in promoting sustainable energy practices in Norway (*Om Enovatilskuddet*, n.d.).

Another incentive available to individuals and businesses is the so-called “green loans”. These loans are provided by banks specifically for environmentally friendly and sustainable projects, such as investing in solar panels. The goal is to encourage people and businesses to make sustainable choices when building new structures or renovating existing ones. The advantages of green loans typically include lower interest rates compared to conventional loans. These loans are often funded by green bonds, which are bonds typically purchased by pension funds. The money from these bonds is earmarked for sustainable purposes, such as financing green loans for consumers or businesses. This system ensures that funds are directed towards projects that have a positive environmental impact, making it financially easier for more people to invest in renewable energy, such as solar (*Hva er grønne lån?*, 2023).

3.0 Literature review

In this section of our paper, we will introduce the concept of bidding zones, synthetic control method and review existing literature on the topic. We will also take a closer look at solar PV in Norway and examine previous literature and historic data.

3.1 Bidding zones

A bidding zone (BZ) is a defined geographical area where electricity prices are uniformly determined by the market, according to European Union Agency for the Cooperation of Energy Regulators (ACER) (n.d.). In Europe, it is common for each country to have its own BZ where prices are guided by supply and demand within each zone (*ACER Has Decided on Alternative Electricity Bidding Zone Configurations*, 2022). Exceptions include Sweden, Denmark, Italy, and Norway, which have multiple BZ within their borders, and Germany and Luxembourg, which share the same BZ (*List of Bidding Zone Borders for HAR Applicable for EU Internal Borders*, 2024). The various BZs have changed many times. Previously, Austria shared the same BZ as Germany and Luxembourg until 2018, when Austria became a separate BZ (*ACER Has Decided on Alternative Electricity Bidding Zone Configurations*, 2022).

Considerable research has focused on Europe's power grid and how BZs influence prices and the development of new energy sources. Egerer et al. (2016) show what the electricity market in Germany could have looked like by using two BZ, one in the north and one in the south, instead of one for the whole country as there currently is. The area in which this proposed northern zone lays, currently has a surplus of production, and would see lower prices with a split. The south would on the other hand face higher prices due to lower production levels. This is assuming the surplus and deficits hold. Although the differences are small compared to wholesale prices and network charges, one can imagine a scenario where the price differences in the various BZ would be significant due to supply and demand. This is quite like what has been observed in Norway following the Russian invasion of Ukraine.

Brouhard et al. (2023) however, believed that an increase in the number of BZ could significantly affect price formation dynamics and result in disadvantageous economic changes for consumers, highlighting potential risks and structural changes in market dynamics over time. In the study, they proposed nine BZ for continental Europe, using clustering methods on locational marginal prices and incorporating factors such as a redispatch effort index and spatial constraints. In the short term, Brouhard et al. believed revising bidding zones can significantly reduce the need for redispatching, which is when grid operators tell power plants to alter their operating schedules (*What Does "Redispatching" Actually Mean?*, 2015). In the end, increasing the number of zones leads to a trade-off between price variability and the proportion of system costs borne by consumers, according to Brouhard et al. Under certain conditions, alternative zone configurations may seem more efficient than the current status quo, especially if the implicit transition costs are disregarded.

Breuer and Moser (2014) discovered that electricity networks function most efficiently when BZ borders align with transmission bottlenecks. As networks change over time, it is essential to periodically adjust BZ borders to reflect shifts in network structure and the geographic distribution of electricity supply and demand. Such adjustments could also have a potential to negatively affect market participants' planning security and hinder investments in renewable energy generation. Notably, if there are significant price differences between BZ, altering the BZ borders would impact the amortization periods for infrastructure investments.

In Norway, the boundaries between different BZ have shifted multiple times over the years. Figure 2 below illustrates the current BZ configuration. While the main lines remain mostly the same, municipalities occasionally switch BZ or are split between two BZ. This happens because the transmission capacity between zones changes over time (*The Power Market*, 2023).

Figure 2: The different electricity zones in Norway. (Derfor har vi prisområder for strøm i Norge, 2024)

As shown in the Figure 3, it is only in recent years that electricity prices have been high, volatile, and significantly different across various BZ. This is primarily due to the increased energy prices in Europe, followed by Russia's invasion of Ukraine, which led to even higher electricity and gas prices as European countries moved away from using Russian gas. This situation resulted in higher energy prices in Norway, particularly in the southern BZ (NO1, NO2, and NO5), due to their proximity to the European electricity market (Holstad, 2023) (*The Power Market*, 2023).

The construction of new power cables from Norway to Germany, Denmark, and the United Kingdom in recent years has led to closer market integration. Consequently, electricity prices in Norway have become more dependent on demand in other European countries. While this integration allows Norway to generate significant revenue by selling electricity at higher prices in Europe, it also means that domestic prices can rise (Hofmann & Lindberg, 2024) (Schrader & Benth, 2022).

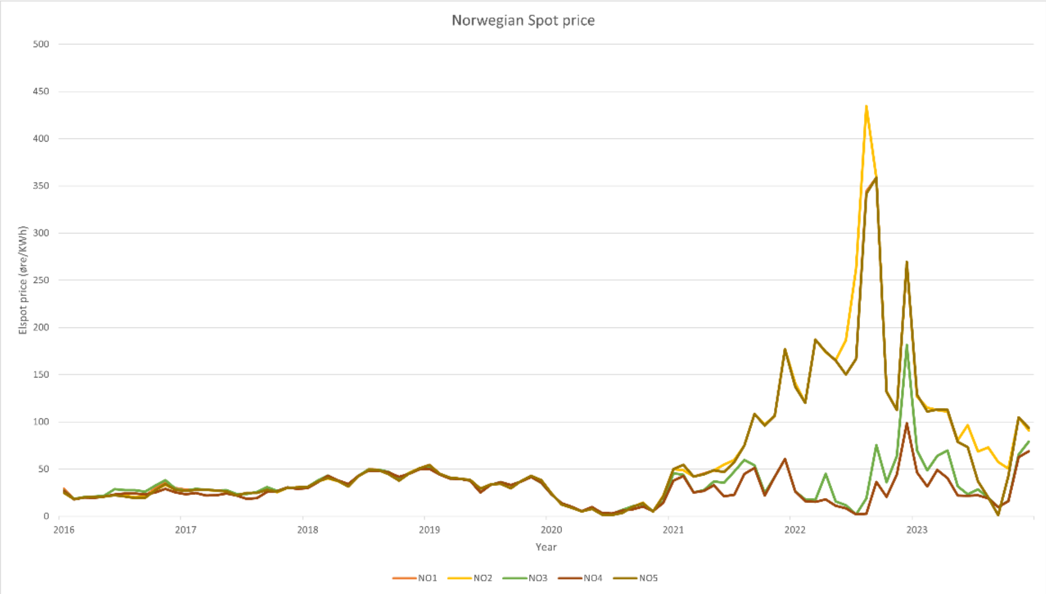

Figure 3: Elspot price of electricity in Norway 2016-2023 (øre/kWh). Source: Nord Pool

Mauritzen (2023) studied the effects of different electricity prices for bidding zones in Norway on electric car adoption, running a natural experiment looking at data for electricity prices compared to registrations of new electric vehicles (EVs) and the subsequent impact on tailpipe emissions. The paper revealed that higher electricity prices can dissuade potential buyers from opting for EVs. This helps highlight the importance of regional variances for consumer decisions that are influenced by electricity prices. Another study that looked at similar characteristics is Fink (2023). While this study was conducted in Sweden, looking at the effects of bidding zones on PV uptake is exactly what we want to quantify in the Norwegian market.

3.2 Solar Energy

"The amount of sunlight that strikes the earth's surface in an hour and a half is enough to handle the entire world's energy consumption for a full year." (*How Does Solar Work?*, n.d.)

There are many ways to harness energy from the sun. In fact, almost all energy originates from the sun (*Energy and Time*, n.d.). In our project, we will focus on photovoltaic generation, also known as PV panels, which is the most common form of solar cells. Another common method is Concentrating Solar-Thermal Power (CSP), which uses mirrors to generate heat that is then converted into electricity.

Sampaio et al. (2017) reviewed the latest advancements in photovoltaic (PV) solar energy through a systematic literature review. They found that the demand for solar PV has grown rapidly since the mid-2000s. What used to be an expensive energy source has now become affordable and reliable. Solar PV is easy to invest in because it has no moving parts and requires minimal maintenance. The study noted that PV solar cells were underrated before 2016, but this view has changed recently due to significant investments from both private and public sectors. The article also discusses the future of solar technology. Crystalline silicon solar cells are currently the most common, but there is great potential for new, cheaper solar cells to emerge. Solar cells are now used in many areas, such as telecommunications, lighting, parking meters, space applications, and agriculture. As prices drop and efficiency improves, their use will continue to grow. Technological advancements and the increasing demand for affordable, eco-friendly, and reliable energy have driven progress in solar cell efficiency.

Today, more than 600 MW of solar power has been installed in Norway, which is expected to produce 459 GWh yearly (*Oversikt over solkraft i Norge - NVE*, n.d.). The amount installed in 2023 is around 303 MW, which is double what was installed in 2022 and equals the total of what had ever been installed in Norway before 2023. Despite this significant growth, it still represents a small fraction of Norway's total electricity production, which was approximately 154 TWh in 2023, primarily sourced from hydropower (*Electricity Production*, 2024).

“The Norwegian Solar Energy Innovation System” (Chasanidou et al., 2021) is a report written by the Norwegian Center for Energy Transition Strategies (NTRANS), University of Oslo, The Norwegian Research Center for Sustainable Solar Cell Technology (SUSOLTECH) and SINTEF in 2021. The report provides an analysis of the solar industry in Norway, with a particular focus on the integration of solar panels into the electricity grid, technological advancements, and market development in the Norwegian market. The report emphasizes Norway's contributions to improving the solar industry through research on more efficient solar power systems and the implementation of new technologies. It highlights the crucial role that universities and research centers in Norway have played in advancing the country's contributions to the solar industry.

Currently, Norway is a relatively small and insignificant player in the global solar market, but the progress made can be significant for Norway's position in the market. The report by Chasanidou (2021) not only comments on Norway's technological contributions but also on the willingness of Norwegians to invest in solar panels in 2019, 2020, and 2021. Although Norway has traditionally relied on hydroelectric power, the electricity crisis in 2021 demonstrated that electricity prices can rise significantly, also in Norway even thug the power production and consumption doesn’t change. Additionally, the cost of solar panel systems has decreased substantially in recent years. This reduction in costs is largely due to new materials, production techniques, efficiency improvements, and inexpensive labor from countries like China (Yerudkar et al., 2024). As a result, many solar panel installations have been set up on private and public buildings. However, this trend has slowed due to several interest rate hikes and more stable electricity prices, especially for residential properties (*Laveste økning i antall plusskunder på over to år - NVE*, 2024).

The significant growth in solar power generation is expected to continue, particularly in the rest of the world, but also in Norway (Solkraft | Statkraft, n.d.). This is largely due to an increased focus on and demand for environmentally friendly energy. It is anticipated that the cost of solar power will continue to decrease, compared to other forms of energy, solar installations are simple and quick to set up and require minimal maintenance as previously mentioned (Solar, n.d.). Despite these advantages, large-scale solar power developments did not commence in Norway until 2018, with an even greater increase observed in 2022 (Oversikt over solkraft i Norge - NVE, n.d.).

Several studies have examined the impact of solar panels and renewable energy sources, such as wind and hydropower, on electricity prices. A study conducted in the United States demonstrated that renewable energy sources contributed to lowering electricity prices. However, it was found that the price of natural gas had the most significant impact on electricity prices. The study in question analyzed the effect of increasing wind and solar power capacity on wholesale electricity prices across various regions in the U.S. from 2008 to 2017. It concluded that while wind and solar energy did help reduce prices, the decline in natural gas prices was the primary driver behind the reduction in wholesale electricity prices. This suggests that, although renewable energy sources play a role in price dynamics, the broader economic influence of natural gas prices is more substantial, at least in the US (Mills et al., 2021).

3.3 Economic and Environmental Impacts

In recent years, having solar panels has been profitable, especially on commercial buildings where the cost of installation is much lower than on private residences, due to economies of scale (Backe, 2023). This can partly be attributed to the recent high and volatile electricity prices were caused by Russia's invasion of Ukraine and their decision to halt gas exports to Europe (European Council, 2024). Before the recent turbulent years, electricity prices in Norway were consistently around 20 - 40 øre (cents) per kilowatt-hour. Now, Statnett estimates that electricity prices will be around 1 Norwegian Krone in 2024 and decrease to an average of 80 øre towards 2028. This is specifically for Southern Norway (NO1, NO2, and NO5) while in Northern Norway (NO3 and NO4), electricity prices are expected to remain lower, with estimates around 20-40 øre per kilowatt-hour (*Fersk analyse fra Statnett*, 2023). This helps incentivize self-producing energy to lower the electricity bill.

According to the Norwegian Water Resources and Energy Directorate (NVE), currently only hydropower and land-based wind power are cheaper than solar power per watt (*Kostnader for kraftproduksjon - NVE*, n.d.). Additionally, the government has a specific subsidy scheme for individuals and businesses that manage to reduce their electricity consumption by a certain percentage (*Solcelleanlegg | Energitiltak | Solenergi*, 2022). Unlike hydropower and most land-based wind farms, solar power installations can be built on existing buildings and structures. This allows for the generation of electricity without developing natural land, utilizing roofs and walls that would otherwise remain unused. Today's solar panels are expected to last over 30 years, with a performance loss of about 0.5 to 0.8 percent per year (*Do Solar Panels Lose Efficiency over Time?*, n.d.). This means that although solar panels are resource-intensive to produce and today must be transported all the way from China, they still have a relatively low CO2 footprint when considering the investment over a 30-year period (Solar, n.d.)

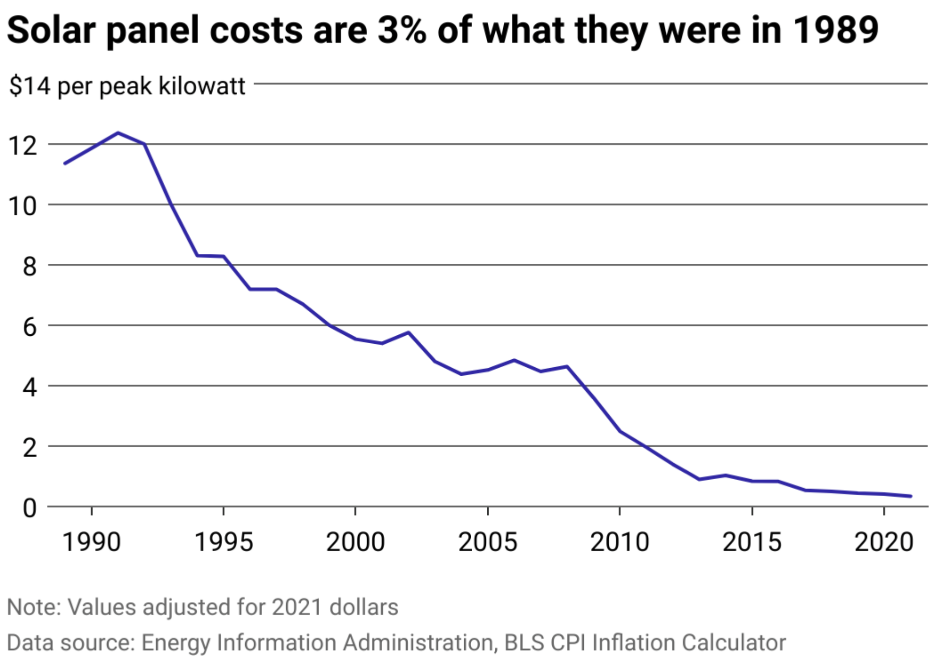

Figure 4: Show the decline in price on solar panels since 1989 (Stacker, 2023).

The reduction in the cost of solar panels over the past few decades has been important for the industry and plays a pivotal role in the global shift toward renewable energy. Technological advancements have increased the efficiency of solar cells, meaning they can convert more sunlight into electricity. This, combined with improved manufacturing processes, has decreased the number of materials and amount of energy required to produce each cell. Economies of scale, driven by increased demand and investments in the solar energy sector, have also played a significant role in cost reduction. As illustrated in the graph in figure 4, the price of solar panels has dropped by 97% in just over 30 years. This is largely thanks to China's major commitment to solar energy in the 1980s and 1990s, continuing to this day (ClimateWire, n.d.).

3.5 Synthetic Control Method (SCM)

The Synthetic Control Method (SCM) has emerged as a useful tool in causal inference, particularly in the fields of policy evaluation and comparative case studies. Introduced by Abadie and Gardeazabal (2003) and further developed by

Abadie, Diamond, and Hainmueller (2010), SCM constructs a synthetic version of the treated unit by optimally weighting control units to estimate what the outcome would have been in the absence of the treatment.

In their 2003 study, Abadie and Gardeazabal constructed a synthetic Basque country from a weighted combination of other Spanish regions to estimate what the Basque economy would have looked like without terrorism. This innovative approach provided a robust counterfactual, allowing the researchers to isolate the economic impact of terrorism. Building on this methodology, Abadie, Diamond, and Hainmueller (2010) applied SCM to assess the impact of California's Tobacco Control Program. They did this by creating a synthetic California using data from other U.S. states to estimate the effect of the tobacco control program on cigarette consumption. This study further demonstrated the versatility and robustness of SCM in policy evaluation and causal inference.

3.4 Difference-in-Difference (DiD)

The Difference-in-Differences (DiD) method is one of the most widely used techniques in empirical research for estimating causal effects in observational studies, where randomized controlled trials are not feasible. This method is frequently applied in fields such as economics, political science, and public health. The DiD method emerged from the necessity to infer causal relationships in the absence of randomized controlled trials. Groundbreaking works by Ashenfelter and Card (1985) and Card and Krueger (1994) established the foundation for DiD applications in labor economics. The core principle involves comparing the differences in outcomes before and after the treatment between treated and control groups to estimate the treatment effect.

The validity of the DiD estimator relies on the parallel trends-assumption, which claims that in the absence of treatment, the treatment and control groups would have experienced similar trends over time. This assumption is crucial for attributing any post-treatment differences to the treatment itself rather than other confounding factors (Lechner & others, 2011). Verifying this assumption involves examining pre-treatment trends through visual inspections or statistical tests to ensure both groups follow parallel paths before the intervention (Rothbard et al., 2023).

Another key assumption is the absence of spillover effects, meaning the treatment administered to the treatment group should not influence the control group. If spillover effects are present, the control group's outcomes might be affected by the treatment, leading to biased estimates. Researchers mitigate this by selecting control groups unlikely to be influenced by the treatment and performing sensitivity analyses to account for potential spillovers (Duflo, 2001) (Miguel & Kremer, 2014).

4.0 Data

To estimate the effect of price divergence between BZ on investments in PV, a balanced dataset is created containing a total of 864 annual observations for 108 Norwegian municipalities that are along the borders between the BZ of NO1, NO5 and NO3. The selection of specific municipalities included in the study will be discussed later, and a list is available in the Appendix. The observation period for our model is driven by data availability for the outcome variable, installed PV capacity, which was provided by NVE (*Oversikt over solkraft i Norge*, n.d.). There were very few installations in any municipality before 2016 in Norway, so the dataset starts from that year. It is important to note that the data reliability varies, as until October 2023, installations could be reported in either AC or DC (M. Nipen, personal communications, February 21st, 2024). All reported installations are included in the dataset.

In the dataset we received from NVE, installed PV capacity is measured in kilowatt peak (kWp), which is a standardized measure of peak power output (*What Is a kWp?*, 2018). We then created a variable for installed PV capacity that is measured in per capita terms to account for the significant variations in Norwegian municipality population sizes, which greatly influence electricity demand, as these factors are positively correlated and demand for PV installations (Zhang et al., 2023). In 2023, the population levels spanned from 208 people in Utsira municipality to 709 037 in Oslo (Statistics Norway, n.d.-a). Because the main goal of this paper is to estimate the effect on PV uptake from price divergence across BZ, the treatment status is determined by a dummy variable, taking the value 1 for municipalities in the low-tariff BZ NO3, and 0 for municipalities in NO1, NO2, or NO5. The three municipalities that span both low- and high-tariff BZs are excluded (Høyanger, Folldal and Tynset), as was not possible to determine where installations within these municipalities are located.

Variables for solar irradiation, median after-tax income and housing structure of municipalities are included as control variables. Irradiation data was obtained from the STRÅNG database provided by the Swedish Meteorological and Hydrological Institute (STRÅNG, n.d.). Data from STRÅNG can be extracted for all geographic locations in Scandinavia since 1999. We extracted hourly data for the main settlement ("tettsted") in each municipality for the period 2011-2016 to maintain consistency, as the resolution for geographical locations changed in 2017. The obtained data was used to create two variables: mean radiation, which refers to the average radiation over the measured period, and radiation variance (σ^2), which accounts for seasonal variation in sunlight exposure that may reduce incentives to invest in PV(Castillo et al., 2016). Both variables are fixed within municipalities over the observation period.

Statistics Norway provides a rich database with information on population size, after-tax income, and housing structure for Norwegian municipalities through their service StatBank Norway (*Statistics Norway*, n.d.-b). After-tax income is reported annually as a median value per household since 2005. Housing structure refers to the share of small households and the data is separated into 5 categories: Detached house, house with two dwellings, row house, linked house and house with 3 or four dwellings, multi-dwelling building and other residential building. The share of detached houses, houses with two dwellings, row houses, linked houses, and houses with three or four dwellings over all dwellings in the municipality is used as a variable, based on the idea that smaller dwellings can adopt PV more easily without much cooperation or agreement between units.

Norway's municipalities have undergone several reforms over the past few years, starting in 2017, with the latest changes to municipalities and counties taking effect on January 1, 2024 (*Nye fylkes- og kommunenummer fra 2024*, 2022). Our dataset spans from 2016 to 2023, covering a period that includes the start of these reforms in 2017. As a result, some values in the dataset have been aggregated to reflect the municipal structure as it was in 2023, ensuring consistency in our analysis despite the administrative changes.

4.1 Border regions

PV uptake across border zones varies significantly in Norway, according to our data. This can partly be explained by underlying differences in control variables, in particular solar irradiation which are significantly lower in the low-tariff BZ in Central- and Northern Norway. Simply comparing one BZ to another would therefore likely not give any meaningful results. As an alternative, the analysis focuses on the region between high-tariff bidding zones NO1, NO5 and NO2 and the low-tariff bidding zone NO3. A similar approach has been used by Fink in Sweden (Fink, 2023) and in Norway for electric vehicle uptake by Mauritzen (2023), as discussed in our literature review. Our selection criteria were mainly driven by existing research on the topic of price divergence in the electricity market, along with data availability.

Like Fink (2023), we have constructed three border regions that are along the borders of the high- and low-tariff BZs in Norway. Our border regions differ from those created by Fink, as there are geographical and demographic differences between Norway and Sweden (Harvey, 2021) that also affect the data and variables. Our study also differs from that of Fink (2023) in that we chose to work with different control variables. Our after-tax income is measured as a median income, and we chose not to include unemployment rates. This is partly due to data availability, but Norwegian unemployment rates are lower and more stable across counties compared to Sweden (*Labour Force Surveys (LFS)*, n.d.) (*Arbeidsledighet i Norge*, n.d.).

In our analysis three different definitions of the bidding zone border are considered, based on their geographical distinctions from the boundary separating the low- and high-tariff BZ areas. The selected municipalities are presented in Figure 3. A list over the municipalities, their BZ and the border region they belong to is included in the appendix in Table 4. Border 1 refers to municipalities that are directly at the border between NO1, NO3 and NO5, where NO1 and NO5 are high-tariff. Border 2 includes municipalities in Border 1, as well as municipalities that are directly adjacent to them. Likewise, Border 3 includes municipalities in Border 2 as well as municipalities that share borders with them. Notably, for Norway this means that in Border 3 we get major Norwegian cities such as Bergen for the high-tariff BZ, and Trondheim in the northern low-tariff BZ. The data for the outcome and control variables are generated by taking the average for each border region. Because the municipalities in the northern and southern border regions are considered separately, values for six different border regions are calculated. The three northern regions are of main interest for the analysis.

Table 1: Descriptive statistics

Variable	Obs.	Unit	Mean	Std. Dev.	Min	Max
Installed capacity per capita	864	kWp	0.0186	0.0417	0	0.4367
Average radiation	864	kWh/m^2	82.5893	5.0435	72.33609	96.13165
Radiation variance	864		20300.90	2062.30	16225.05	26024.5
Median after tax-income	864	NOK	526028	54413.48	376000	724000
Housing structure	864	%	0.9043	0.0831	0.4859	1

4.2 Alternative estimation

Since our original definitions for the border regions include cities like Bergen and Trondheim for the third border region, we wanted to run an alternative estimation without these municipalities to see the effect the cities had on our results. This was further motivated by the fact that the second largest municipalities in the donor pool and treatment unit had much lower populations compared to the municipalities hosting the cities mentioned above.

5.0 Methodology

With the theoretical groundwork for our research approach laid out, we will now focus on how to answer the question we are looking at. Our plan is to use quantitative research to analyze panel data of solar PV generation and relevant covariates for the Norwegian market. As previously explained, we are looking at data in the range of 2016-2023 which we believe will highlight the recent increased interest and development of the technology as well as the recent price divergence of electricity prices in the different bidding zones in Norway. This should give us interesting results when we create synthetic border regions to show the effects on price divergence on PV uptake.

5.1 Quantitative research model

Quantitative research, through the application of a panel data model, examines causal relationships by leveraging numerical data over time and across different entities. This methodological approach will be applied in our thesis on solar PV uptake, as it not only allows for the analysis of large datasets but also considers the dimensions of time and entity-specific variability. Panel data models are particularly adept at dissecting the nuanced impact of price and price volatility on investment patterns, enabling a more precise generalization of findings across the diverse landscape of solar PV installations. Our data, sourced from authoritative market and governmental reports, provide a solid foundation for testing our hypothesis regarding the dynamic relationship between price factors and investment trends in the solar PV sector.

5.2 Synthetic Control Method

The Synthetic Control Method (SCM) was developed in 2003 to improve upon the difference-in-difference approach for policy evaluation. By rather than selecting a single non-intervention comparison unit, the SCM constructs a synthetic control unit by using a weighted average of multiple non-intervention units. This method provides a more accurate and reliable benchmark for assessing the impact of the policy intervention (Abadie & Gardeazabal, 2003). Unlike comparative case studies, SCM provides a formal and entirely data-driven method for selecting control units. This approach minimizes researchers' opportunities to bias the results through p-hacking or selective searches. Additionally, SCM can account for time-varying unobservable confounders. Assessing the fit of the SCM model is also straightforward because the outcome values for the treated unit and its synthetic control group should ideally be identical during the pre-treatment period. Moreover, the condition that weights are non-negative and sum to one prevents extrapolation and makes the interpretation of the results more straightforward.

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

Equation 1

The synthetic control (SCG) group is defined as “a weighted average of the units in the donor pool.” (Abadie, 2021). To calculate the model, we use the formula above in Equation 1. Here, the first term on the left side of the equation represents the outcome of the treated synthetic control group at time t. In our case, this refers to the synthetic PV production for municipalities in BZ NO3. The second term on the right side of the equation is the summation that constitutes the synthetic control. This is a weighted combination of the outcomes from the control group, which includes the municipalities in BZ NO1 and NO5 (Abadie, 2021).

In this analysis, the equation helps us construct a synthetic control group to estimate the PV production for municipalities in the treated zone (NO3). The synthetic control group is created from a combination of municipalities in the control zones (NO1 and NO5), weighted by ωj to best replicate the characteristics of the NO3 municipalities before any intervention. By comparing the actual outcome for NO3 with the synthetic control, we can estimate a counterfactual scenario to what would have happened in the absence of the intervention (Abadie, 2021). The SCM is built on two key assumptions: non-interference and the constraint of weights to non-negative values. The non-interference assumption states that the treatment status of the treated unit *i* is unaffected by the donor units *j*. An example of this could be if a municipality invests substantial funds and resources into developing a plan to become more environmentally friendly by investing in new technology, solar and bike paths. There is a high likelihood that this will influence neighboring municipalities through shared infrastructure or market dynamics (Bonander et al., 2021) (Albalate et al., 2021). The second assumption that weights must be non-negative and sum up to one, ensures that the donor pool consists of a relatively small number of comparison units (Abadie & Gardeazabal, 2003) (Abadie, 2021).

Despite all the advantages of SCM, several contextual and data requirements need to be considered when applying this method. First, SCM should not be used when the treated unit is an outlier, which occurs when an outcome or predictor value falls outside the range of all potential control variables or if high volatility in outcomes can negatively impact the ability to detect the treatment effect. Also, the units that have experienced significant idiosyncratic shocks should be excluded from the donor pool. For example, if a municipality that has experienced a sudden economic downturn due to the closure of a major employer, resulting in a significant change in local income levels and economic activity witch again will result in a substantial change in the outcome variable, should be eliminated (Bonander et al., 2021).

Some potential problems using SCM include difficulty in finding suitable control units that closely match the treated unit in the pre-treatment period, especially if the treated unit has unique characteristics. If there are unobserved confounders that vary over time and affect the outcome, SCM might not fully account for these, potentially leading to biased estimates. Another challenge is ensuring that the weights used to construct the synthetic control are appropriate and do not lead to overfitting. SCM also requires a substantial amount of high-quality data, and any deficiencies in data availability or accuracy can undermine the reliability of the results. (Bonander et al., 2021) (Albalate et al., 2021)

In addition to contextual considerations, applying synthetic controls requires the use of aggregate data. Microlevel data can be aggregated to derive the necessary outcome or predictor values. It is also crucial to have sufficiently long preintervention and postintervention periods. If the pre-treatment period is too short, there is a risk of overfitting the model to the limited data available and if the postintervention period is too brief, the full extent of the treatment effect might not be possible to captured. This means that accurate and comprehensive data collection is essential for reliable results. Aggregating micro-level data should be done carefully to ensure that it accurately represents the broader trends and patterns at the aggregate level. The quality of the aggregated data must be high, as any inaccuracies or inconsistencies can significantly impact the analysis. (Bonander et al., 2021) (Albalate et al., 2021)

It is also important that the chosen pre-intervention and post-intervention periods must be long enough to provide a clear view of the trends before and after the treatment. A short pre-treatment period might not fully capture the baseline trends, leading to overfitting, where the synthetic control matches the treated unit too closely due to limited data points and a short post-intervention period might not allow enough time to observe the full impact of the treatment, potentially missing long-term effects or delayed responses (Abadie et al., 2010).

5.2.1 The Problem of overfitting in SCM

Angrist and Pischke (2009) discuss overfitting in their book Mostly Harmless Econometrics: An Empiricist's Companion, emphasizing the importance of model simplicity to ensure robustness and generalizability. They highlight the risks of overfitting when too many variables or units are used, which can obscure the true causal effects (Angrist & Pischke, 2009). As mentioned above, overfitting can also occur if the pre- or post-intervention periods are too short.

5.2.2 Addressing overfitting in SCM

To address the potential for overfitting in the synthetic control method (SCM), we used placebo tests. Placebo tests involve re-estimating the treatment effect by artificially assigning the treatment to a different time period than the actual treatment period. This helps to verify that the observed treatment effect is not due to random fluctuations or model overfitting. If the placebo period shows a significant treatment effect, it suggests potential overfitting or model misspecification (Abadie et al., 2010).

5.3 Difference-in-Difference (DiD)

We have chosen to supplement our analysis with use of Difference-in-Difference. This approach was selected to further evaluate the impact of electricity prices on individuals' willingness to invest in PV across bidding zones. The DiD method allows us to compare changes in outcomes before and after the intervention between the treatment group (North) and the control group (South) across our three definitions of border regions. By employing this method, we can control for both time-related factors affecting both groups and fixed differences between the groups that do not change over time. Specifically, we used the same borders (border 1, 2, and 3) and the same variables as in the SCM. We did however omit the solar irradiance variables as these do not vary over time.

$$Y_{it} = \alpha + \beta_1 Post_t + \beta_2 North_i + \delta(Post_t * North_i) + \varepsilon_{it}$$

Equation 2

The equation above, Equation 2, is the one used in our analysis. The outcome variable Y_{it} represents the investment in solar panels for unit i at time t, showing changes over time and between groups. The constant term α indicates the baseline level of the outcome for the control group before the intervention. The dummy variable $Post_t$ is 1 after the intervention and 0 before, capturing time effects that impact both groups. $North_i$ is a dummy variable that is 1 for the treatment group (North) and 0 for the control group (South), capturing fixed differences between the groups. The interaction term $Post_t * North_i$ measures the causal effect of the intervention, showing how changes in the outcome differ between the treatment and control groups. The error term ε_{it} captures random disturbances and unobserved factors affecting the outcome, assumed to be independently and identically distributed.

The DiD method relies on the parallel trend's assumption, which says that the treatment and control groups would have followed the same trajectory over time without the intervention. Violation of this assumption can bias the results. Selection bias can occur if groups differ systematically in ways that affect the outcome. Time-varying confounders, spillover effects, and heterogeneous treatment effects can also pose challenges. Accurate model specification and reliable data collection are essential to mitigate these issues (*Difference-in-Difference Estimation | Columbia Public Health*, 2016).

5.4 Model estimation

To implement our models in practice, we used the statistical software StataSE 18. The synthetic control method is not a part of the base software but can be downloaded as an additional package. The synthetic control method was implemented using the 'synth' command, which allows for the creation of a synthetic control group by optimizing weights assigned to control units. For the difference-in-difference, the 'xtdidregress' command in Stata was employed.

6.0 Results

This section presents our findings through the regression results from the SCM estimations separately for the three different definitions of the BZ border regions. Then, we present the results found using the DiD-regression. The results are then discussed separately and together in our discussion section.

6.1 Our findings

Installed capacity for the three borders and its SCG are illustrated in Figure 5. The composition for the SCG is documented in Table 9 in the Appendix. The scale for kWp per capita is different in Figure 5a and 5b & 5c. This is because the model predicts a much larger increase for the synthetic unit for the different borders.

The municipalities that were used in creating the control groups vary for our model. For the first border, only a few municipalities are selected. For the second and third however, the model selects weights for almost all members of the donor pool, which can indicate overfitting of the model where it is capturing noise as part of the model as opposed to the underlying trend. The graphs in Figure 5a, 5b and 5c show a good level of fitting during the pretreatment period for the first couple years in all variations of the model, with a slight deviation as we approach the treatment period. The deviation is largest for border 2, where we see it deviate by 0.002 kWp or 13.27% from the observed variable in 2020. In 2021 the changes are insignificant at less than 0.001 kWp for all three borders.

When we enter the treatment period, the trend for the synthetic unit clearly diverges from the observed values. In the first year of 2022 and beyond we see increased differences between the observed and synthetic values in border 1 & 2, where the changes are measured at 0.069 and 0.027 kWp respectively, with border 3 close behind border 2 at 0.015 kWp. These are both statistically and economically significant effects, further increasing in 2023 with border 1 having a 0.22 kWp or 266.69% increase. Border 2 and border 3 also have sizable effects in 2023 with deviations of just over 0.1 kWp for border 2 and 0.04 kWp for border 3. This amounts to a relative change of 165.96 and 92.50 per cent respectively, underscoring the substantial economic impact.

When evaluating the representability of the SCG, it is important to look at the predictor values for the SCG and compare it to the values of the treated units. The results are presented in Table 3 in absolute terms. In our model, the greatest difference is installed capacity in 2017 for the first border region, where the synthetic unit takes a value of 0 instead of the 0.0005019 from the treated unit. Otherwise, median after-tax income variable differs the most between the SCG and the treated units. The difference is interestingly largest for the second border region; however, this only amounts to a difference of 33 154.90 NOK or 6.32%. For border region 3, installed capacity in 2019 and 2021 differ 0.00013 and 0.00029 kWp per capita, but this only amounts to a difference of 1.68 and 1.65 per cent for the two variables. All other variables are within 1% of the treated units.

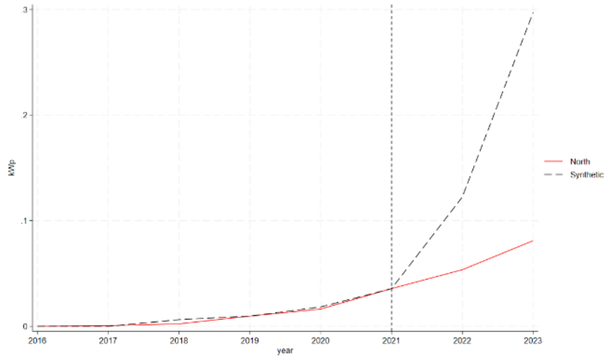

Figure 5 (a)

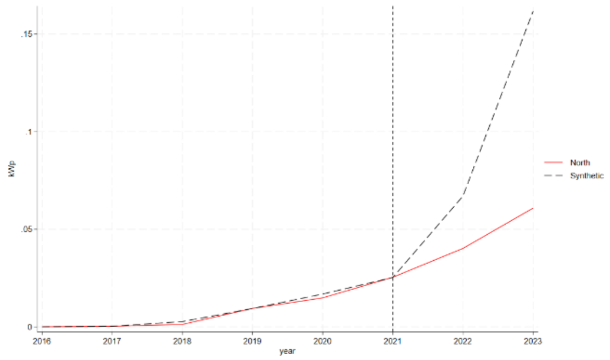

Figure 6 (b)

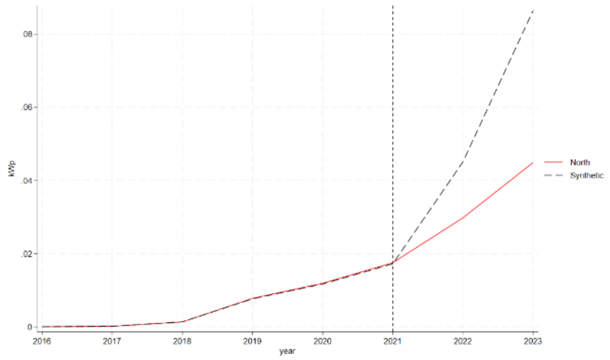

Figure 7 (c)

Please do note again that the scales in figures 4 (a-c) are different on the Y-axis for installed capacity.

Table 2: Absolute and Relative treatment effect

	Border 1	**Border 2**	**Border 3**
Absolute (kWp)			
2021	6.483E-05	0.00010982	0.00028828
2022	-0.06887854	-0.02682939	-0.0153193

2023	-0.21620572	-0.10099082	-0.04154484
Relative (%)			
2021	0.18 %	0.43 %	1.64 %
2022	-128.60 %	-66.74 %	-51.40 %
2023	-266.69 %	-165.96 %	- 92.50%

Table 3: Predictor variables

	Border 1		**Border 2**		**Border 3**	
	Treated	**Synthetic**	**Treated**	**Synthetic**	**Treated**	**Synthetic**
Average radiation	81.04164	81.50945	81.25154	81.23975	81.14858	80.90441
Radiation variance	19362.7	19321.36	19621.21	19653.62	19744.54	19685.56
Median income	510677.1	509590.6	524837.7	491682.8	533163.6	531687
Housing structure	0.9390165	0.9371389	0.923519	0.921924	0.9025982	0.9000928
Installed capacity 2017	0.0005019	0	0.0002865	0.0002863	0.000147	0.0001467
Installed capacity 2019	0.0096364	0.0096185	0.0094632	0.0094027	0.0077916	0.0076605
Installed capacity 2021	0.0356752	0.0356104	0.0254168	0.025307	0.0175246	0.0172364

6.2 Alternative estimation results

After running our original model, we also wanted to test the effect of leaving out the major cities to better understand the impact of cities in such estimations as well as comparing this to previous literature. Like the original third border region, the municipalities included are those sharing border with municipalities in border region 2 as well as those included in border region 2. The exceptions here are Bergen and Trondheim, which were excluded. The SCG composition is slightly different from that of border region 3, but it still picks weights for most municipalities suggesting potential overfitting. The fitting is still very good for the pretreatment period, holding at under 1% from the treated unit.

When we enter the treatment period, we see a similar divergence from the treated unit as for border 3, however the treatment effect is slightly larger. This results in an effect of 0.02143 and 0.05704 kWp, or 68.36% and 117.91% for 2022 and 2023. While we still see a potential overfitting of the model, the predictor variables that are used for this alternative estimate all hold in the range of under 1% from that of the treated unit. This is similar to what was found for the original third border, with a slightly better fit for the installed capacity in 2019 and 2021.

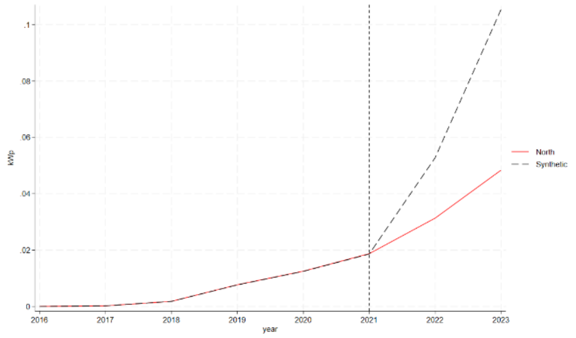

Figure 8: Alternative estimation for the third border region

Table 4: Absolute and Relative treatment effect for alternative estimation

	Alt. Border 3
Absolute (kWp)	
2021	0.00012835
2022	-0.02143275
2023	-0.05703657
Relative (%)	
2021	0.69 %
2022	-68.36 %
2023	-117.91 %

Table 5:Predictor variables for alternative estimation

	Alt. border 3	
	Treated	**Synthetic**
Average radiation	81.12305	81.04035
Radiation variance	19730.25	19712.91
Median income	533106.9	532625.8
Housing structure	0.9151889	0.9141444
Installed capacity 2017	0.0002153	0.0002171
Installed capacity 2019	0.0077156	0.0076563
Installed capacity 2021	0.01873	0.0186016

6.2 DiD-results

The DiD-regression results are presented in Table 6. We ran regressions for all three border regions with and without the control variables of median after-tax income and housing structure. The solar irradiation variables were ignored, as these are constant across time within each municipality. Across all three border region definitions, the *average treatment effect on the treated (ATET)* has a statistically significant negative effect on the outcome variable of PV uptake both with and without the control variables at the 1% level. The treatment effect is greatest for border 1, where treatment results in a reduction in PV uptake of 0.12 kWp when control variables are included.

The housing structure control variable is statistically significant for border 2 with a p-value of less than 0.01. For this statistically significant result, there is a positive association to the outcome variable as expected. The same is the case for median income for border 3.

Table 6: DiD-regression results

	Border 1		**Border 2**		**Border 3**	
	(1)	(2)	(3)	(4)	(5)	(6)
ATET	-0.120***	-0.121***	-0.092***	-0.093***	-0.083***	-0.075***
	(0.0361)	(0.0356)	(0.0211)	(0.0209)	(0.0141)	(0.0141)
Income		-1.97e-07		-5.32e-08		1.73e-07***
		(3.47e-07)		(4.17e-07)		(5.03e-08)
Housing		-1.283681		1.482118***		0.0383714
		(1.163588)		(0.3504667)		(0.0281772)
Constant	-1.39e-17	1.306859	7.18e-06	-1.353208	5.06e-06	-0.1216901
	(0.0096183)	(1.217508)	(0.0055317)	(0.4080531)	(0.0036426)	(0.0409278)
Year FE	Yes		Yes		Yes	

Robust standard errors in parenthesis

**** p<0.01*

We also ran a placebo test, and to test if the underlying assumptions are violated, we performed parallels trends. For the placebo, we assume that treatment occurs in 2019, two years before the actual treatment.

Table 7: Parallel trends assumption

	Border 1	**Border 2**	**Border 3**
South	-17.63618**	-13.35669***	-9.797111***
	(7.119184)	(4.06238)	(2.63836)
North	0	0	0
	(.)	(.)	(.)
Year	0	0.0098562	0.0040188
	(.)	(.)	(12.08882)
South_Year	0.0146817***	0.0011262	0.0044966
	(.0027014)	(.)	(11.6835)
North_Year	0.0059363**	-0.005497	-0.0003615
	(.0022718)	(.)	(11.88789)
Constant	-11.97174**	-8.791241***	-7.375621***
	(4.582114)	(2.342097)	(1.465812)

Robust standard errors in parenthesis

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

From Table 7 we see that for border 1, the significant coefficients for South_Year and North_Year suggest that there are pre-treatment differences in trends between the treatment (North) and control (South) groups. This could indicate a violation of the parallel trends-assumption. For the second border, the lack of standard errors, t-values, and p-values for the interaction terms is due to omission by collinearity. This makes it difficult to draw conclusions from this model. Finally, for the third border region the non-significant coefficients for year, South_Year and North_Year suggests that there are no pre-treatment differences in trends between the treatment and control groups. This supports the parallel trends assumption.

For the placebo test, we see significant estimates for all both specifications of all three borders. The significant negative effect of the placebo treatment suggests that there may be pre-existing trends or other factors influencing the outcome variable prior to the actual treatment year (2021). This finding raises concerns about the parallel trends-assumption, suggesting that something else is driving difference in PV uptake in 2021.

Table 8: DiD Placebo test

	Border 1		Border 2		Border 3	
	(1)	(2)	(3)	(4)	(5)	(6)
ATET	-0.0882495***	-0.0883884***	-0.0679374***	-0.0695957***	-0.0588403***	-0.0474265***
	(0.0281259)	(0.0282189)	(0.0162682)	(0.0165671)	(0.0108049)	(0.0107405)
Income		-2.54e-07		-7.14e-08		2.43e-07***
		(3.50e-07)		(4.33e-07)		(6.08e-08)
Housing		-1.214727		1.495505***		0.039959
		(1.269881)		(0.367934)		(0.0271172)
Constant	-2.78e-17	1.269344	7.18e-06	-1.356948***	5.06e-06	-0.158342***
	(0.0095574)	(1.317236)	(0.0055041)	(0.4249421)	(0.0036289)	(0.043012)
Year FE	Yes		Yes		Yes	

Robust standard errors in parenthesis

*** p<0.01*

7.0 Discussion

This part will discuss the implications of our findings and future expansions into PV in Norway or other countries in Europe. Additionally, the use of SCM, DiD and our definitions of border regions is critically evaluated.

7.1 Implications of our findings

Our main finding in this study is that the electricity price divergence in 2021 and beyond reduces PV uptake in the BZ of Central Norway by 92.50% to 266.69%

depending on the border region definitions. This supports previous findings that highlight how important economic factors are for the uptake of PV in Norway and elsewhere (Xue et al., 2021) (Fink, 2023).

Positive effects on the supply balance are countered by the rapid divergence in PV uptake across the country. This disparity could hinder the country's ability to fully realize its PV potential and successfully transition to renewable energy generation. This could turn problematic in the long run, considering that Norway’s energy surplus is expected to decrease over the coming years, according to the latest estimates (*Fortsatt positiv kraftbalanse mot 2028 - NVE*, 2024). According to the same estimates, an increase in solar PV production will play a role in avoiding a deficit in the Norwegian market. This highlights further the importance PV will play in Norway’s energy mix going forward.

Our findings indicate a pretty radical increase in solar investments in the synthetic units. The model also appears to predict that population density negatively impacts investment, which is not what we would expect based on previous literature on the topic (Zhang et al., 2023) (Fink, 2023). Our results may have been skewed by the fact that the combined populations in the second and third treated units are vastly larger than the combined population of the first treated units. The first northern border region consisted of 15 municipalities, whereas the second border region has 31 municipalities. The third border region consists of 51 municipalities. The combined population also spans from 68 940 in 2023 for border region 1 to 188 969 in border region 2 and 651 862 in border region 3 for the same year. The third border region also includes the city of Trondheim and its surrounding municipalities, further skewing the results from this definition of the border region. The city of Bergen is also part of the third southern border region; however, this municipality was assigned a weight of 0.1% by the model in the estimation.

While we tried to account for this in our alternative estimation, but the results are still skewed towards a negative correlation between population levels and PV uptake in our models. This may suggest that our models did not properly handle the underlying trends in PV uptake, or that the market has yet to mature. This is further identified in our difference-in-difference model, where our placebo test found that the parallel trends assumption may be violated and that other factors are driving investments other than price divergence.

On the other hand, Norway has overall seen a rapid increase in PV installations over the past few years. In Norway as a whole, the total effective capacity of PV doubled both in 2022 and 2023, according to NVE. In 2023, just over 300 MW of solar was added to the Norwegian grid system, which amounted to a doubling of the installed effect (*Solkraft*, 2024). It should therefore be interesting to try this model again after the market has matured. This does however hinge on a continued price divergence between the BZ in Norway.

7.2 Feasibility of synthetic control method

While the estimated results from the model are both economically and statistically significant, the question of feasibility of the model for our thesis remains. As discussed previously in our thesis, the synthetic control method has certain requirements that need to be met for the model to accurately predict the counterfactual. The validity of this study would be compromised if policymakers were able to foresee the impact of price divergence on PV adoption when bidding zones were created as a result of the introduction of market-based power trading back in 1991 (*The Power Market*, 2023). This is unlikely to have been the case, seeing that there were almost no grid-connected installations before 2014 in Norway (*Electricity Production*, 2024). This is also supported by the fact that the price divergence in Norway took place in 2021, many years after the liberalization of the market. Since the price divergence were mostly caused by market factors outside of Norway, as discussed previously, it is unlikely policymakers could foresee this.

Due to the nature of our estimation model, there is a risk that the SCG may not accurately represent the treatment unit. This problem could arise if there are significant variations in outcome and control variables among the members of the SCG, which would be simply averaged out by the estimation method (Abadie, 2021).

Placebo tests were conducted with an intervention period in 2019 instead of 2021. The model is the same, except the removal of the variable for installed capacity in

2021 and the treatment period starting in 2019 instead of 2021. The resulting graphs are displayed in the Appendix under Figure 7a, 7b and 7c. This was done to check for significant deviations in outcome levels for the SCG and treated units before the actual treatment period in 2021. The significant deviations start after 2021, supporting our thesis about the price divergence in 2021 is the driving force for PV uptake between BZ.

7.3 Border region selection

When choosing the most appropriate border region definition, Border 3 yields the best results when comparing the outcome data for the treated unit and SCG in the pre-treatment period. However, the overall treatment effect is lowest in this region. This is likely largely due to the significant population increase in the third border region with the inclusion of Trondheim. While a wider border definition may seem advantageous, it introduces growing imbalances in predictor balance. For our study, this imbalance specifically affects solar radiation levels, as the low-tariff BZ is situated further north compared to the southern counterparts. Since it is crucial to minimize underlying differences between the treated unit and its high-tariff counterparts for accurate model estimation, a narrower border region definition is preferred.

When measuring treatment effectiveness, the first border region shows most promise. This border region does not suffer from large deviations in the pretreatment period either, except for having a non-zero value for the 2017 installed capacity. It also has the largest treatment effect at just under 0.3kWp, and the weights are distributed to a select few in the control group.

With the goal of a small definition of the border region and the fact that the second and third suffer from likely overfitting, border 1 should be the preferred definition in our study. For this definition the outcome levels are higher due to the low-density populations and the model better captures the underlying trend from what we can tell.

8. Conclusion

In this study, we explored the impact of electricity price divergence on the uptake of photovoltaic (PV) systems in Central Norway using a synthetic control method

(SCM). Our findings indicate a significant reduction in PV uptake due to price divergence, highlighting the critical role of economic factors in renewable energy adoption. However, while our model predicts an increase in PV uptake, we approach these results with caution due to potential overfitting. This caution is particularly warranted given the model's assignment of weights to almost all municipalities in the synthetic control group (SCG) for the second and third border regions. The results from our DiD regression also further have cause for concern, as the parallel trends-assumption may be violated.

The rapid increase in PV installations across Norway suggests a growing interest and investment in solar energy, driven by factors such as falling technology costs and supportive policies. However, the disparity in PV adoption across different regions poses a challenge to achieving a balanced and equitable energy transition. This regional variation could hinder Norway's ability to fully harness its solar potential and maintain its energy surplus overall.

Our use of SCM in this study, while providing valuable insights, also underscores the need for careful selection of control group municipalities. The significant variation in population and other characteristics among the municipalities included in the SCG could have influenced our results. Additionally, the layout and administrative structure of Norwegian municipalities differ significantly from those in Sweden, where Fink (2023) conducted her study. Fink (2023) mentions in her article that the model estimation is not feasible for Norway, as the solar PV market in Norway only emerged in 2020 when the prices started to diverge. We respectfully disagreed after looking at the raw data, and wanted to try and estimates despite this suggestion. Our results do however indicate that they may have been right after all.

The implications of our findings are significant for policymakers and stakeholders. As Norway and other European countries consider dividing into BZs, the risk of imbalances in PV uptake within countries becomes evident. Similar to findings in Sweden by Fink, the unequal incentivization of PV adoption in high-tariff areas could limit PV expansion to specific parts of the country, potentially undermining the overall green transition goals. Not fully utilizing PV potential could jeopardize the achievement of EU climate targets related to renewable electricity generation and carbon emission reduction, as well as the goal of 8 TWh per year by 2030 set by the Norwegian Parliament.

In conclusion, our study highlights the complexities and challenges associated with modeling PV uptake using SCM. While our findings offer valuable insights into the effects of electricity price divergence, they also point to the need for ongoing refinement of models and methodologies. Future research should focus on improving the selection of control groups and exploring additional factors that may influence PV adoption. By addressing these limitations, we can better inform policymakers and stakeholders working towards a sustainable energy future.

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Appendix

Table 9: SCG Composition

Name	Border 1	Border 2	Border 3	Alt. Border 3
Alvdal	0,0 %	0,4 %	0,3 %	0,3 %
Alver	0,0 %	1,0 %	0,5 %	0,5 %
Askøy	0,0 %	0,0 %	0,3 %	0,4 %
Aurland	0,0 %	0,2 %	28,7 %	20,4 %
Austevoll	0,0 %	0,0 %	0,2 %	0,2 %
Austrheim	0,0 %	0,4 %	0,0 %	0,3 %
Bergen	0,0 %	0,0 %	0,1 %	0,0 %
Elverum	0,0 %	0,0 %	0,6 %	0,6 %
Engerdal	0,0 %	1,4 %	0,8 %	1,0 %
Etnedal	0,0 %	0,0 %	0,4 %	0,5 %
Fedje	7,0 %	5,6 %	0,1 %	0,3 %
Gausdal	0,0 %	1,6 %	0,6 %	0,5 %
Gjøvik	0,0 %	0,0 %	0,8 %	0,6 %
Gol	0,0 %	0,0 %	0,6 %	0,5 %
Gulen	0,0 %	1,0 %	0,3 %	0,4 %
Hamar	0,0 %	0,0 %	0,7 %	0,6 %
Hemsedal	0,0 %	0,7 %	0,3 %	0,3 %
Hol	0,0 %	0,0 %	0,7 %	0,6 %
Kvam	0,0 %	0,0 %	0,8 %	0,8 %
Lillehammer	0,0 %	0,0 %	7,9 %	2,0 %
Luster	0,0 %	1,0 %	0,8 %	0,6 %
Lærdal	0,0 %	1,0 %	0,4 %	4,8 %
Løten	0,0 %	0,0 %	0,5 %	0,7 %
Masfjorden	2,1 %	1,7 %	0,3 %	0,5 %
Modalen	0,0 %	1,1 %	3,4 %	2,0 %
Nord-Aurdal	0,0 %	0,4 %	0,3 %	0,3 %
Nord-Fron	11,9 %	1,3 %	0,5 %	0,6 %
Nordre Land	0,0 %	0,0 %	0,5 %	0,6 %
Os, Innlandet	0,0 %	0,3 %	0,3 %	0,2 %
Osterøy	0,0 %	0,0 %	0,4 %	0,5 %
Rendalen	0,0 %	2,5 %	0,3 %	0,4 %
Ringebu	0,0 %	1,7 %	0,7 %	0,8 %
Ringsaker	0,0 %	5,2 %	0,6 %	0,7 %
Røros	51,3 %	7,1 %	1,7 %	6,0 %
Samnanger	0,0 %	0,0 %	23,5 %	22,9 %
Sogndal	14,0 %	0,3 %	0,3 %	0,3 %
Stange	0,0 %	0,0 %	0,6 %	0,5 %
Stor-Elvdal	0,0 %	0,5 %	0,4 %	0,4 %
Sør-Aurdal	0,0 %	0,0 %	0,3 %	0,3 %
Sør-Fron	13,5 %	2,6 %	1,0 %	1,5 %

Tolga	0,0 %	0,4 %	0,2 %	0,2 %
Trysil	0,0 %	45,4 %	1,4 %	1,4 %
Ullensvang	0,0 %	0,0 %	2,0 %	1,1 %
Ulvik	0,0 %	0,0 %	0,7 %	0,8 %
Vaksdal	0,0 %	8,4 %	0,2 %	1,9 %
Vang, Innlandet	0,0 %	0,8 %	0,4 %	0,4 %
Vestre Slidre	0,0 %	0,5 %	0,2 %	0,4 %
Vik, Sogn	0,0 %	0,6 %	0,5 %	0,4 %
Voss	0,0 %	0,9 %	0,5 %	0,5 %
Våler (Innlandet)	0,0 %	0,0 %	0,3 %	0,5 %
Østre Toten	0,0 %	0,0 %	1,0 %	3,5 %
Øyer	0,0 %	1,3 %	0,9 %	1,3 %
Øygarden	0,0 %	0,7 %	0,3 %	0,3 %
Øystre Slidre	0,0 %	0,6 %	0,4 %	0,4 %
Ål	0,0 %	0,0 %	0,5 %	0,4 %
Åmot	0,0 %	0,9 %	1,3 %	1,1 %
Årdal	0,0 %	0,5 %	7,4 %	9,9 %

Table 10: Border region and BZ

Name	BZ	Border 1	Border 2	Border 3	North/South
Alvdal	NO1	1	0	0	0
Alver	NO5	0	1	0	0
Askvoll	NO3	0	1	0	1
Askøy	NO5	0	0	1	0
Aurland	NO5	0	1	0	0
Austevoll	NO2	0	0	1	0
Austrheim	NO5	0	1	0	0
Bergen	NO5	0	0	1	0
Bremanger	NO3	0	0	1	1
Dovre	NO3	1	0	0	1
Elverum	NO1	0	0	1	0
Engerdal	NO1	0	1	0	0
Etnedal	NO1	0	0	1	0
Fedje	NO5	1	0	0	0
Fjaler	NO3	1	0	0	1
Fjord	NO3	0	1	0	1
Gausdal	NO1	0	1	0	0
Gjøvik	NO1	0	0	1	0
Gloppen	NO3	0	1	0	1
Gol	NO5	0	0	1	0
Gulen	NO5	1	0	0	0
Hamar	NO1	0	0	1	0
Heim	NO3	0	0	1	1

Hemsedal	NO5	0	1	0	0
Hitra	NO3	0	0	1	1
Hol	NO5	0	0	1	0
Holtålen	NO3	1	0	0	1
Hyllestad	NO3	1	0	0	1
Indre fosen	NO3	0	0	1	1
Kinn	NO3	0	1	0	1
Kvam	NO5	0	0	1	0
Lesja	NO3	0	1	0	1
Lillehammer	NO1	0	0	1	0
Lom	NO3	1	0	0	1
Luster	NO5	1	0	0	0
Lærdal	NO5	0	1	0	0
Løten	NO1	0	0	1	0
Malvik	NO3	0	0	1	1
Masfjorden	NO5	1	0	0	0
Melhus	NO3	0	1	0	1
Meråker	NO3	0	1	0	1
Midtre Gauldal	NO3	1	0	0	1
Modalen	NO5	1	0	0	0
Molde	NO3	0	0	1	1
Nord-Aurdal	NO1	0	1	0	0
Nord-Fron	NO1	1	0	0	0
Nordre Land	NO1	0	0	1	0
Oppdal	NO3	1	0	0	1
Orkland	NO3	0	1	0	1
Os, Innlandet	NO1	1	0	0	0
Osterøy	NO5	0	0	1	0
Rauma	NO3	0	1	0	1
Rendalen	NO1	1	0	0	0
Rennebu	NO3	1	0	0	1
Rindal	NO3	0	1	0	1
Ringebu	NO1	0	1	0	0
Ringsaker	NO1	0	1	0	0
Røros	NO1	1	0	0	0
Samnanger	NO5	0	0	1	0
Sande, Møre og Romsdal	NO3	0	0	1	1
Sel	NO3	1	0	0	1
Selbu	NO3	0	1	0	1
Skaun	NO3	0	0	1	1
Skjåk	NO3	1	0	0	1
Sogndal	NO5	1	0	0	0
Solund	NO3	1	0	0	1
Stad	NO3	0	1	0	1
Stange	NO1	0	0	1	0
Stjørdal	NO3	0	0	1	1
Stor-Elvdal	NO1	1	0	0	0
Stranda	NO3	0	1	0	1

Stryn	NO3	1	0	0	1
Sula, Møre og Romsdal	NO3	0	0	1	1
Sunndal	NO3	0	1	0	1
Sunnfjord	NO3	1	0	0	1
Surnadal	NO3	0	1	0	1
Sykkylven	NO3	0	0	1	1
Sør-Aurdal	NO1	0	0	1	0
Sør-Fron	NO1	1	0	0	0
Tingvoll	NO3	0	0	1	1
Tolga	NO1	1	0	0	0
Trondheim	NO3	0	0	1	1
Trysil	NO1	0	1	0	0
Tydal	NO3	1	0	0	1
Ullensvang	NO5	0	0	1	0
Ulstein	NO3	0	0	1	1
Ulvik	NO5	0	0	1	0
Vaksdal	NO5	0	1	0	0
Vang, Innlandet	NO1	1	0	0	0
Vanylven	NO3	0	0	1	1
Verdal	NO3	0	0	1	1
Vestnes	NO3	0	0	1	1
Vestre Slidre	NO1	0	1	0	0
Vik, Sogn	NO5	1	0	0	0
Volda	NO3	0	1	0	1
Voss	NO5	0	1	0	0
Vågå	NO3	1	0	0	1
Våler (Innlandet)	NO1	0	0	1	0
Ørland	NO3	0	0	1	1
Ørsta	NO3	0	0	1	1
Østre Toten	NO1	0	0	1	0
Øyer	NO1	0	1	0	0
Øygarden	NO5	0	1	0	0
Øystre Slidre	NO1	1	0	0	0
Ål	NO5	0	0	1	0
Ålesund	NO3	0	0	1	1
Åmot	NO1	0	1	0	0
Årdal	NO5	0	1	0	0

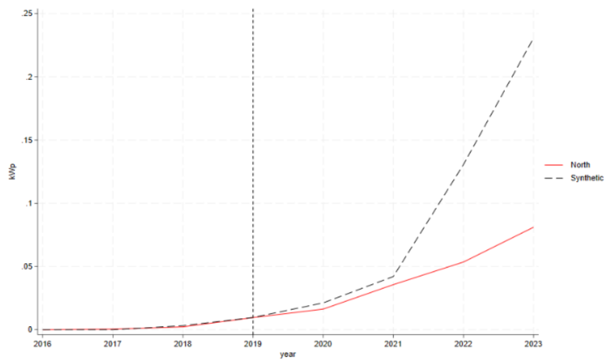

Figure 9 (a)

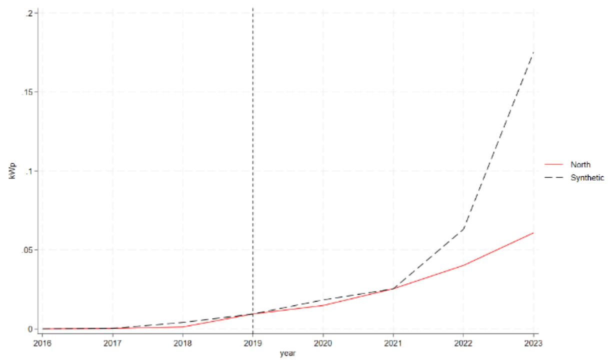

Figure 10 (b)

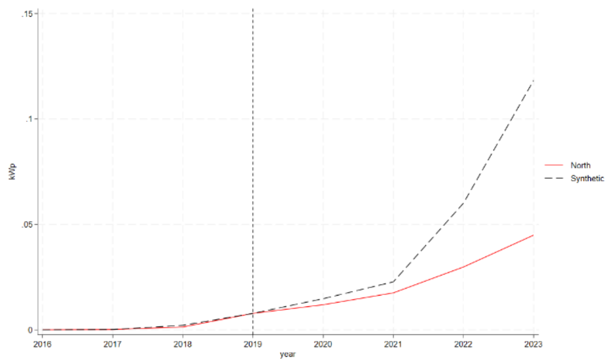

Figure 11 (c)