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Connected but Divided?

The Impact of the Flow-Based Method on Incentives to Invest in Electricity and Wind Power in Sweden

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Abstract

Sweden needs to expand its electricity production to meet a growing demand, driven by the electrification of society. Wind power is one of the most viable options for expansion, as a renewable energy source with low costs. It does, however, tend to "cannibalize" its own revenues, since electricity prices drop during periods of high wind quantity. The Nordic countries recently implemented the flow-based capacity calculation method, which influence prices by determining how much transmission capacity is available. It is assumed to lead to price convergence in the region. This method has the potential to reduce cannibalization and can increase the incentives to invest in wind. This study investigates how incentives to invest in electricity and wind power have changed under the new method. This is done by using time series models across Sweden's bidding zones. The results suggest that relative incentives to invest in wind power have increased in Northern Central Sweden. Contrary to expectations, incentives to invest in electricity have declined in Northern Sweden.

Keywords: Flow-based Method, Cannibalization Effect, Unit Revenues, Wind Power, Swedish Electricity Market

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1 Introduction

The electrification of Sweden is in full force, driven by the green transition and the need to decarbonize industry. In response, the government must expand national electricity production to meet a growing demand and strengthen Sweden's competitiveness. Wind power plays an important role in this development, as it is a renewable energy source with relatively low costs, and Sweden benefits from favorable wind conditions (Prop. 2023/24:105).

Sweden's electricity market is divided into four bidding zones (SE1, SE2, SE3, and SE4), each with its own electricity price. Since bidding zones are interconnected, prices in one zone are influenced not only by local supply and demand conditions, but also by those in neighboring zones. The extent of price differences depends on the transmission capacity between zones (Svenska Kraftnät, 2024c). As the transmission capacity is limited, trade is sometimes restricted, leading to regional price differences.

The Nordic countries recently introduced a new method for calculating the transmission capacities to use the existing physical electricity grid more efficiently. Simply put, this method better coordinates how capacity is used in the current network, allowing for more cross-border exchange between bidding zones. This method is called the flow-based method and was implemented on October 30, 2024.[1] It is estimated to increase the transmission capacity in the existing Nordic electricity grid by an amount equivalent to ten years of physical grid expansion (Svenska Kraftnät, 2024e). In other words, by changing how capacity constraints between bidding zones are calculated, the current grid can be used more efficiently, without building new infrastructure. In essence, this could lead to price convergence across the bidding zones on the Nordic market, if electricity can more efficiently flow to high-price areas (Svenska Kraftnät, 2024d). This should in turn influence the incentives to invest in electricity, both in the aggregate as well as in terms of geographical location and energy source.

Before the implementation of the new method, Svenska Kraftnät and the other Nordic transmission system operators, ran a simulation exercise to see how the flow-based method could affect electricity prices. The results indicated that prices in the Nordic countries tended to converge, with higher prices in SE1, SE2, and SE3, thus confirming the theoretical expectations (Svenska Kraftnät, 2024d). Such a price convergence would be beneficial for producers in northern Sweden and provide stronger incentives to invest in electricity production. These areas are also expected to face the largest increase in demand due to the electrification of the steel industry (Energiföretagen, 2023).

One of the most important sources for expanding electricity production in Sweden is wind power. But an increasing share of wind in the power system creates new challenges. Wind power is exposed to a cannibalization effect, where increased production during windy periods pushes electricity prices downwards, reducing the revenue per megawatt-hour produced (Liebensteiner and Naumann, 2022; López Prol, Steininger, and Zilberman, 2020). In principle, the flow-based method could help mitigate this effect by allowing excess supply to be exported more efficiently, thereby reducing the price-suppressing effects of high wind output within the zones.

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[1] The flow-based method is also a part of Regulation (EU) 2015/1222

This is also mentioned as a key reason for introducing the method in the Nordic countries. The flow-based method is argued to better integrate renewable energy sources, such as wind, into the electricity market by making it more flexible to deal with fast changes in supply levels (Bergman, 2024). But, to the best of our knowledge, no previous research has examined how the flow-based method affects the cannibalization effect and the relative incentives to invest in wind power.

Using real market data, we investigate how the flow-based method has actually influenced incentives to invest, both in electricity and in wind power specifically. We analyze how these effects differ across Swedish bidding zones. In particular, we aim to answer the following research questions:

i. How has the flow-based method affected the general incentives to invest in electricity across Sweden's bidding zones?

ii. How has the flow-based method affected the relative incentives to invest in wind power across Sweden's bidding zones, particularly through changes in the cannibalization effect?

This study analyzes the day-ahead market from January 1, 2023, to March 31, 2025. The flow-based method was introduced on October 30, 2024, meaning that the data cover five months with the new method. We specify two linear regression models to examine how the flow-based method has influenced incentives to invest in (i) electricity in general and (ii) wind power specifically, across Sweden's bidding zones. We study how revenues, shaped by electricity prices and modeled as a function of supply and demand, change when the flow-based method is introduced, and how this, in turn, affects incentives to invest in electricity and wind power. The first model uses electricity unit revenue as the dependent variable, while the dependent variable in the second model is the difference between wind unit revenue and electricity unit revenue.

We find that incentives to invest in electricity have decreased in northern Sweden (SE1 and SE2) following the introduction of the flow-based method, while no significant impact is observed in the south (SE3 and SE4). This is in contrast to the simulation results done by the Nordic transmission system operators (Energinet et al., 2024). The findings raise concerns that the new method can reduce expansion of electricity production in Sweden.

When focusing on incentives to invest in wind specifically, we find suggestive evidence of the presence of a cannibalization effect across all Swedish bidding zones. Wind unit revenue is typically lower than average electricity unit revenue, regardless of capacity calculation method. However, the results suggest that wind power performs relatively better under the flow-based method in SE2. In contrast, there is suggestive evidence of a decrease in the relative incentives to invest in wind power in SE4. No significant effects are found in SE1 or SE3. Overall, this suggests that the first period with the flow-based method has not been effective in promoting investments in either electricity or wind power within the Swedish context.

In addition, this study finds that the timing of wind production throughout the day significantly impacts relative wind unit revenue. To our knowledge, this phenomenon has not been accounted for in the previous cannibalization literature, but it has, however, been discussed. When using a model similar to those in the established literature, we initially found a positive relationship between wind production and the relative wind unit revenue. This contradicts the concept of cannibalization, suggesting a model misspecification. When investigating wind production in detail, we noticed that the distribution of production differs significantly between low-wind and high-wind days. On high-wind days there is typically high wind output during midday and the afternoon, when demand is the highest. Thus, the timing of production impacts relative revenue during the day and should be accounted for. To address this, we developed a new model that separates the cannibalization effect from the effect of the timing of wind production. As our approach is rather primitive, we encourage future research in this area.

The Swedish context is particularly interesting because it has a high share of wind power compared to many other countries, and the production mix differs across its bidding zones. Our focus on Sweden is also driven by data availability. Thus, we cannot state if the flow-based method leads to price convergence across all Nordic bidding zones. Still, Sweden is interesting in its own right, since our results are directly relevant for the ongoing political debate about expanding electricity production. Wind power is expected to play a key role in this expansion, but the incentives to invest are affected by the cannibalization effect. While previous studies have investigated this effect, a specific focus on Sweden is lacking.

2 Background

2.1 Electricity Production in Sweden

Sweden's electricity supply mainly comes from hydro power (38%), followed by nuclear power (29%) and wind power (24%). Smaller shares comes from thermal power (7%) and solar power (2%) (Statistics Sweden, 2025a).[2] The share of wind power in the electricity generation mix has increased significantly in Sweden over the last decade, from around 4% in 2011 (Swedish Energy Agency, 2012).

The electricity production mix differs across bidding zones, as shown in Figure 1. The predominant production source in SE1 and SE2 is hydropower, while SE3 mainly relies on nuclear power, and SE4 primarily generates wind power. In absolute terms, most electricity is produced in SE3, whereas SE4 has the lowest production. When accounting for consumption in each zone, it can be observed that SE1 and SE2 typically produce more electricity than they consume, while SE3 and SE4 consume more than they produce. As a result, SE1 and SE2 are primarily exporting zones, whereas SE3 and SE4 are typically importing zones.

Looking more specifically at wind power, SE2 produces the highest amount in absolute terms. However, SE4 has the largest share of wind in its production mix.

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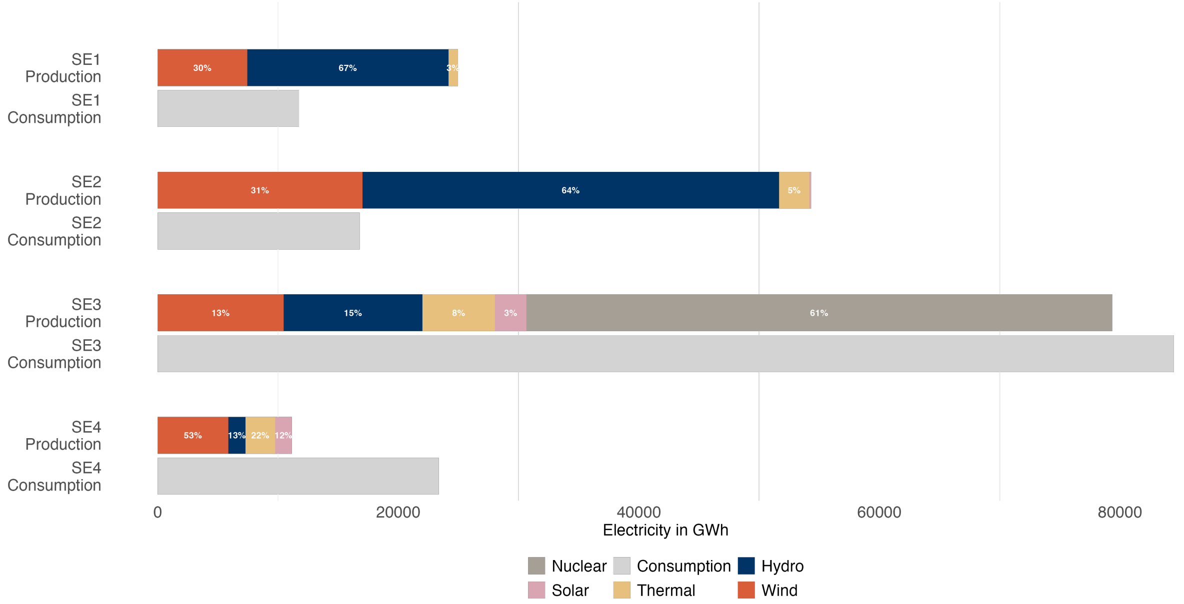
[2] Thermal power represent conventional thermal power, such as industrial back-pressure, gas turbines, cogeneration, and condensing power (Statistics Sweden, 2025a).



Each bar indicates the share (in percentage) of each production source within the total production. Data is collected from (Statistics Sweden, 2025a).

Figure 1: Total Electricity Production and Consumption by Bidding Zone in 2024.

2.1.1 Characteristics of Electricity Supply

Different types of electricity production have important distinctions. They are typically grouped into dispatchable and non-dispatchable sources. Dispatchable sources, such as hydro, nuclear, and thermal power, can adjust their output based on demand. In contrast, non-dispatchable sources, such as wind and solar power, depend on external factors (mainly the weather) and cannot be controlled in the same way (Holmberg and Tangerås, 2023). Furthermore, the degree of flexibility, meaning how quickly and easily a source can adjust its output, varies among dispatchable sources. Hydro power is a highly flexible source. It can respond quickly to short-term changes in demand because energy is stored in reservoirs and can be released when needed (Jaraitė et al., 2019). This means hydropower producers can adjust their output at short notice to market conditions, without incurring significant costs (Holmberg and Tangerås, 2023). Thermal power also provides some flexibility. A small share of Sweden's electricity production comes from thermal power, which includes various sources such as coal, oil, biomass, and waste. These sources each have different flexibility characteristics. In contrast, nuclear power is dispatchable but not very flexible. Nuclear plants generally operate continuously and cannot adjust their output quickly in response to daily price changes. Instead, they primarily adjust their production over longer time frames, for example during maintenance periods (Jaraitė et al., 2019).

2.2 Electricity Consumption in Sweden

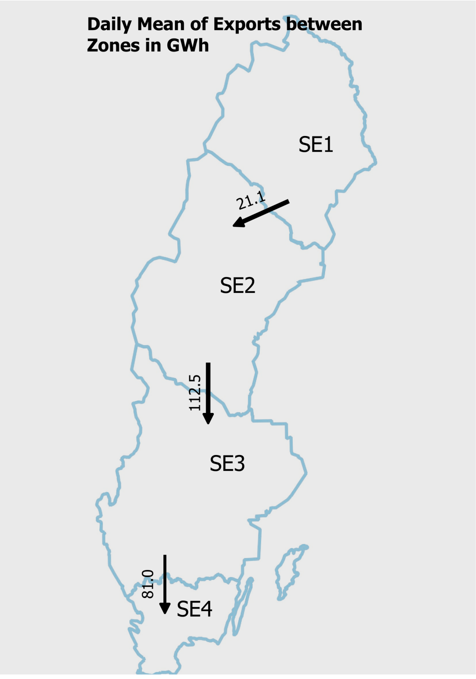
The demand for electricity in Sweden has been relatively stable over the past decades. However, a significant increase is expected going forward, driven largely by electrification. For example, when replacing fossil fuels with electricity in industrial processes and the transport sector (Bergman et al., 2022).

Consumption patterns differ between bidding zones (see Figure 1). The highest electricity use is found in SE3, where Sweden's largest cities in terms of population are located. In 2024, the total electricity consumption was around 84,500 GWh in SE3, compared to 11,800 GWh in SE1, 16,800 GWh in SE2, and 23,400 GWh in SE4 (Statistics Sweden, 2025a). Most electricity is consumed by the residential, service, and other sectors (i.e. households, construction, and agriculture) and by the industrial sector, which each account for a similar share of total consumption. The transport sector follows, accounting for a smaller share of consumption (Swedish Energy Agency, 2023).

Electricity demand also varies by season and weekday. For instance, lower temperatures generally increase demand, as electric heating is common in Swedish households, leading to higher consumption during the winter. In contrast, demand tends to be lower on warmer days. Weekday patterns also exist, with demand typically higher on weekdays than on weekends (Sandberg, 2024).

2.3 Electricity Exchange between Bidding Zones

The exchange of electricity between Swedish bidding zones varies. SE1 and SE2 mainly export electricity, while SE3 and SE4 primarily import it. Figure 2 shows the average daily net (scheduled) exports between selected bidding zones from January 1, 2023 to October 29, 2024. The largest export volumes occur between SE2 and SE3. This is also where the main transmission bottleneck affecting Sweden within the Nordic Electricity system is located. In addition, all Swedish bidding zones trade electricity with neighboring zones outside the country. As a result, congestion can occur at international transmission lines, for example, between Sweden and Norway, along the Hasle link connecting SE3 and NO1.



Note: Data is collected from Nordic RCC (2025)

Figure 2: Average Daily Net Scheduled Exports between Sweden's Bidding zones

2.4 The Electricity Market

Electricity can be traded at different times before its delivery, across different market. Most electricity is traded on the day-ahead market, where electricity is bought and sold for delivery the upcoming day. Buyers and sellers submit bids for each hour specifying the quantities, prices, and bidding zone in which they wish trade electricity the following day (Svenska Kraftnät, 2024a). So far, the flow-based method is only implemented at the day-ahead market.

Electricity in Sweden is primarily traded on Nord Pool, which is part of a common European market. This market is divided into bidding zones. The division is based on network constraints, especially where congestion is likely to occur. These zones are connected through a system known as market coupling, which allows buyers in one zone to purchase electricity from sellers in another, as long as there is enough capacity on the transmission lines connecting the zones (All NEMO Committee, 2024).

Each seller and buyer submit their bids to the common market. A single algorithm, called Euphemia, is used to match supply and demand across all zones. Euphemia collects all bids and determines which to accept in order to maximize total economic surplus, while respecting transmission capacity constraints in the electricity market. The result is one market clearing price for each bidding zone (All NEMO Committee, 2024). Therefore, the transmission capacity plays a key role in price formation across the region.

2.5 Capacity Calculation Method

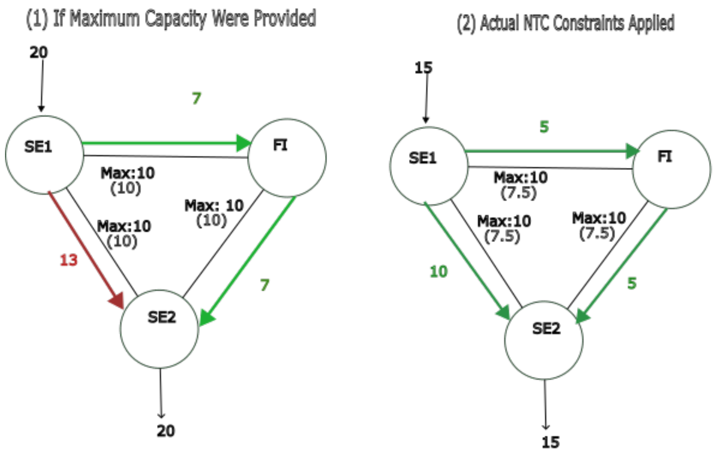
Because bidding zones are interconnected, prices in one zone are influenced not only by local supply and demand but also by conditions in neighboring zones. The extent of this influence depends on available transmission capacity. As a result, the method used to calculate transmission capacity directly affects electricity prices. In the Nordic region, this capacity calculation is done by the Transmission System Operators (TSO's) in Sweden, Norway, Denmark, and Finland.

2.5.1 Net Transfer Capacity Method

Until October 29 2024, transmission capacity was calculated using the Net Transfer Capacity (NTC) method. We illustrate how the NTC method works using a modified example based on Energinet et al. (n.d.)

Consider a simplified power system consisting of only three interconnected bidding zones: SE1, SE2 and FI. Each transmission line (SE1-SE2, SE2-FI, and SE1-FI) is assumed to have a maximum physical capacity of 10 MW, as shown in Figure 3.

Suppose electricity is injected in SE1 with the goal of being consumed in SE2. In principle, electricity can be transferred either directly from $SE1 \rightarrow SE2$ or indirectly via $SE1 \rightarrow FI \rightarrow SE2$. This creates two potential transfer paths, allowing for a theoretical total exchange capacity of up to 20 MW from SE1 to SE2 (Energinet et al., n.d.).



Note: The value in parentheses denotes the capacity made available to the market. The maximum physical capacity is always 10, but the offered capacity differs between models. Illustration based on Energinet et al. (n.d.), adapted by the authors.

Figure 3: Illustration of the NTC Network Example.

Electricity flows according to the laws of physics, not contractual arrangements. In other words, electricity typically travels the shortest route. In our example, this mean most electricity would flow on the direct route $SE1 \rightarrow SE2$. In the examples shown in Figure 3, assume that around two-thirds of the electricity would flow directly from $SE1 \rightarrow SE2$, while the remaining one-third would take the longer route via FI (i.e. $SE1 \rightarrow FI \rightarrow SE2$), if electricity was injected in SE1.

If the TSO's assign a maximum capacity of 10 MW to each transmission line, it gives the market the possibility to make contractual agreements to trade 20 MW between SE1 and SE2, and 20 MW could then be injected into SE1. However, because most electricity naturally flows on the direct path, around 13 MW would flow directly on the SE1-SE2 line. This exceeds that line's physical limit, causing an overload. An example of this is shown in the left panel of Figure 3.

To prevent overloads and ensure operational security, the NTC method reduces capacity on transmission lines by adding a safety margin. This guarantees that no line is overloaded, even if electricity flows along the shortest path. In the previous example, where two-thirds would flow directly via $SE1 \rightarrow SE2$, the TSO's would limit the transmission capacity so that no more than 10 MW could flow directly on that line. Since this direct flow represents two-thirds of the total injection, the total injection in SE1 would be limited to 15 MW. To simplify, assume the safety margin is distributed equally on both possible routes from SE1. Then a safety margin of 2.5 MW would be subtracted from each transmission line. This is illustrated in the right panel in Figure 3.

The safety margin imposed by the NTC method to ensure grid stability is called the Transmission Reliability Margin (TRM). This margin is added to each cross-border transmission line separately. The capacity available for trading between two zones, known as the Net Transfer Capacity, is then defined as:

$$NTC = TTC - TRM,$$

where TTC (Total Transfer Capacity) is maximum technical capacity on a transmission line, and TRM reflects uncertainties to ensure operational security (ETSO, 2000). In the example shown in the right panel of Figure 3, the TTC on the SE1-SE2 line is 10 MW, the TRM is 2.5 MW, resulting in an NTC of 7.5 MW.

The NTC approach helps maintain operational security on the grid, but it often leads to underutilization of available transmission capacity. This method treats each border as an independent line and only provides market participants with the NTC values. It does not reflect how electricity actually flows through the network. As a result, it tends to limit cross-border trade more than necessary (Svenska Kraftnät, 2024b).

2.5.2 Flow-Based Capacity Method

As of October 30, 2024, the Nordic region adopted the flow-based method to calculate transmission capacities in the day-ahead market. Unlike the NTC method, the flow-based method better reflects how electricity actually flows through the grid. It considers all cross-border transmission lines simultaneously and coordinates how capacity is used across the network, allowing for a more efficient use of the existing infrastructure (Svenska Kraftnät, 2024b).

The flow-based method relies on two key components: the remaining availability margins (RAM) and the power transfer distribution factors (PTDF's). RAM defines how much electricity can safely flow through each critical transmission line. PTDF's describe how an injection of electricity in one bidding zone affects flows on each line. In other words, a PTDF indicates the percentage of a unit of electricity that will flow on a specific transmission line when it is injected or withdrawn somewhere in the network (Svenska Kraftnät, 2024b).

The flow-based method provides the market with all PTDF's and RAM's for each transmission line and zone. This gives participants more information of how electricity will flow when injected in a specific zone, and how these flows will affect the available transmission capacity. While under the NTC-method, the only information the market received was the net transfer capacity on each cross-border transmission line. With the extra information under the flow-based method, the market can better assess the entire network. This enables better coordination and ensures that the available capacity can be used more effectively.

A simplified way of thinking about it is to look at Figure 3 again. The NTC method is forced to add a safety margin (i.e. TRM) on each transmission line to ensure operational security. Therefore, this method often withholds capacity from the market (Svenska Kraftnät, 2024b). In contrast, the flow-based method considers all transmission lines at the same time and coordinates cross-border exchanges in line with actual physical constraints on the grid. As a result, the safety margins on each transmission line required under the NTC method can be reduced.

In reality, the flow-based calculations involve multiple bidding zones across the interconnected European market, with several critical transmission lines in each zone. As the number of network components increases, so does the complexity to predict market outcomes. In addition, not all information about the critical transmission lines are given to the market due to security reasons, which reduce transparency and introduce additional uncertainties (Cherney and Seleznev, 2025). Therefore, it may be difficult for market participants to navigate the market under the flow-based method (Lernstad, 2024).

It is worth noting that the flow-based method coordinates electricity flows to maximize overall welfare across the entire region. This can lead to non-intuitive flows, where electricity flows from a high-price zone to a low-price zone. While this may seem inefficient, it can help free up capacity for more beneficial flows elsewhere in the system, allowing the grid to be used more effectively overall (Energinet et al., n.d.).

3 Theoretical Framework and Related Literature

In this section, we begin by outlining theoretical frameworks that can explain how the flow-based method may change incentives to invest in electricity and wind power. We then review relevant empirical studies addressing these mechanisms. Based on this, we formulate our hypotheses. For simplicity, we assume that the flow-based method increases transmission capacity and flows from low- to high-price areas.

3.1 Incentives to Invest in Electricity

3.1.1 Theoretical Framework: Law of One Price

When transportation costs decrease, such as through increased transmission capacity in the electricity market, the prices of identical goods tend to converge. This principle is explained by the transport-adjusted Law of One Price (Ejrnæs and Persson, 2000). It states that the price difference between two markets should not be greater than the transportation cost. The same logic applies in the Nordic electricity market with the introduction of the flow-based capacity calculation method. By making better use of the current transmission grid and increasing cross-border capacity, the flow-based model allows electricity to flow more efficiently from low-price to high-price areas. This promotes price convergence across the region (Svenska Kraftnät, 2024b). In turn, this can influence where it is most profitable to invest in electricity. In a Swedish context, low-price exporting zones such as SE1 and SE2 are expected to experience price increases, while high-price importing zones like SE4 may see a price decrease. The impact on SE3 is less certain, as it both imports electricity from zones with lower prices but also exports electricity to Norway and SE4, which typically has higher prices. As a result, if transportation costs on SE3's main transmission lines are reduced evenly, the overall impact on prices in SE3 is likely small.

3.1.2 Previous Empirical Findings

In Europe, the flow-based method was first introduced on the day-ahead electricity markets of Belgium, France, Germany/Austria/Luxembourg and the Netherlands (i.e. Central Western Europe) in 2015. Ovaere et al. (2023) examined the effect of introducing the flow-based method in this region on cross-border exchange and price convergence. The authors applied both a regression discontinuity in time framework and time series analysis to examine the short- and long-term effects, respectively. Their findings suggest that in the short run, cross-border exchange volumes increased and prices converged across the region. Exporting countries experienced price increases, while importing countries saw price decreases.[3]

The flow-based method was only recently introduced in Sweden, and to the best of our knowledge no empirical study has yet focused on its outcomes in Sweden or the other Nordic countries. However, before the implementation, the Nordic transmission system operators ran a simulation for almost two years, where they evaluated the flow-based method's impact on prices and expected flows. The simulation took the orderbooks (i.e. all buy and sell offers shaping the supply and demand curve) and computed an equilibrium price and expected flows for each bidding zone, according to both the NTC and flow-based method. The simulation assumed that the orderbooks remained fixed, meaning it did not account for how market participants may change their bidding strategies in response to the new method. Therefore, the simulation results should be interpreted as indicative rather than predictive of actual market outcomes (Svenska Kraftnät, 2024e).

The simulation results suggest that the electricity prices in the Nordic countries would converge under the flow-based method, which is in line with theory. Specifically, the simulation showed that electricity prices, on average, increased in SE1, SE2, and SE3, while the prices decreased in SE4 (Svenska Kraftnät, 2024d; Svenska Kraftnät, 2024e).[4] [5]

3.2 Relative Incentives to Invest in Wind Power

3.2.1 Theoretical Framework: The Cannibalization Effect

In any market, classical economic theory states that an increase in supply (ceteris paribus) leads to a reduction in prices. In electricity markets, this principle is reflected in the merit-order effect. Figure 4 illustrates this phenomenon. Bids are ranked by short-run marginal costs, which are typically illustrated by a step-shaped supply curve (i.e. the merit order curve). Variable renewable energy sources, such as wind and solar, have a marginal cost around zero (López Prol and Schill, 2021), placing them at the bottom of the merit-order curve.

When a large amount of cheap renewable power enters the market, the merit order curve shifts to the right, lowering electricity prices. The effect on price may be large as demand is very inelastic.

This merit order effect causes electricity prices to decrease during periods of high wind production, as low-cost wind displaces more expensive sources in the supply curve (Kooten, 2016). As a result, wind power can experience a cannibalization effect, where it undermines its own unit revenue.

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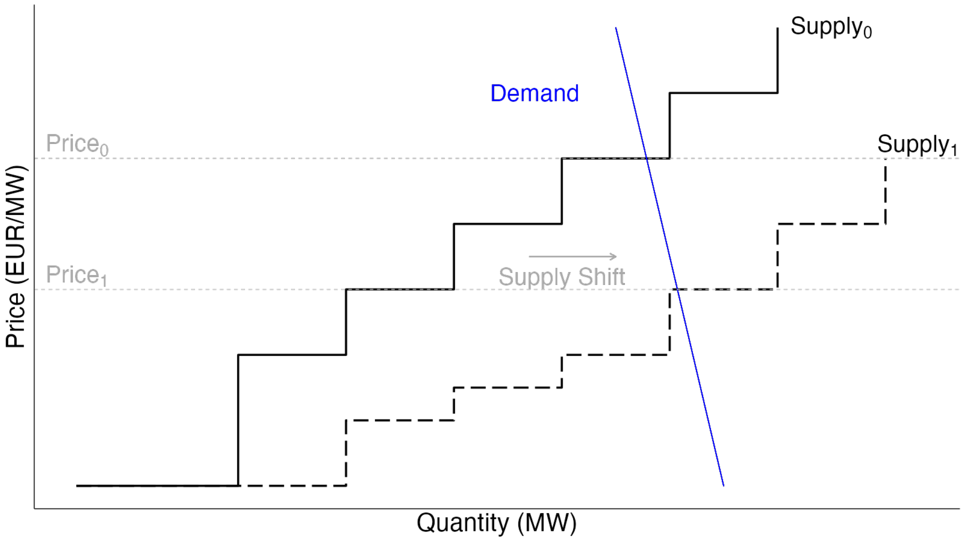
[3] In the long run, when controlling for changing market conditions, the positive effects appears to diminish. One possible explanation is a reduction in transmission capacity allocated to critical lines.

[4] Data on day-ahead prices and net positions from the simulation is publicly available for each zone and hour at Nordic RCC (2025)

[5] The price increase in SE3 is somewhat unexpected as this is usually considered a high-price zone in a Swedish context. However, this can be explained by SE3 exporting more electricity to NO1 under the flow-based method, where NO1 tends to have higher electricity prices than SE3 (Svenska Kraftnät, 2024b).



Note: Demand is assumed to be inelastic in the short run. When electricity supply increases due to variable renewable power generation the supply shifts from the solid to the dashed line. The graph is based on Kooten (2016).

Figure 4: Illustration of The Merit Order Effect

Since some electricity producers are flexible, they can adjust their production in response to prices, making their average revenues per MWh less sensitive to fluctuations in supply. Wind power, on the other hand, is inflexible and cannot adjust its production to match prices. As a result, wind revenues tend to be more sensitive to wind output compared to other producers. This is known as the relative cannibalization effect, where high wind output disproportionately reduce wind revenue, which in turn reduces the incentives to invest in wind power compared to other sources.

Flow-Based Method and Cannibalization: More transmission capacity should allow excess electricity from one zone to be exported to others, helping to balance supply and demand more effectively. This should reduce local price suppression during periods of high wind output, which can decrease the cannibalization effect and strengthen incentives to invest in wind power.

However, increased interconnection also allows wind production from neighboring zones to flow into the domestic zone more easily. If wind conditions are similar across zones, high production in one area can coincide with high production in others. This simultaneous increase in supply in multiple zones can depress prices more broadly and increase what is known as the cross-border cannibalization effect (Stiewe et al., 2025). The scale of this effect depends on the level of transmission capacity and how wind production align across zones.

The flow-based method increases available transmission capacity, which can influence both effects. It can reduce the cannibalization effect by spreading surplus domestic wind supply more effectively in the system, but it may also increase cross-border cannibalization if wind supply surpluses align across zones. As a result, its impact on relative incentives to invest in wind depends on the balance between these two opposing effects (Stiewe et al., 2025).

3.2.2 Previous Empirical Findings

Previous studies have identified a cannibalization effect of wind power in different contexts (e.g., López Prol, Steininger, and Zilberman, 2020; Liebensteiner and Naumann, 2022).[6] The relative cannibalization effect is usually estimated by focusing on how the value factor of wind power is influenced by wind power production. The value factor is a ratio of the unit revenue of a electricity source to the unweighted average electricity price, indicating how much of the electricity price is captured by the electricity source.[7] One central and influential study in the wind cannibalization literature is López Prol, Steininger, and Zilberman (2020). The authors find evidence of both an absolute and relative cannibalization effect of wind and solar on the Californian market throughout the years 2013-2017, using a time series econometric analysis. With regards to a relative cannibalization effect, their results suggest that for each percentage point (p.p.) increase in wind market share, the value factor of wind tends to decrease by 0.58 p.p..

In addition, Ajanaku and Collins (2023) examines the Pennsylvania-New Jersey-Maryland (PJM) regional market during 2016-2019 using quantile regression, with OLS results provided as a benchmark. Their findings stand out, as few studies report a positive relationship between wind production and the wind value factor. The OLS estimates suggest that one additional GWh of wind production is associated with a 0.05 p.p. increase in the wind value factor. However, their quantile regression results reveals a negative relationship at higher quantiles of the value factor distribution. Their results implies that the cannibalization effect emerge when electricity prices are high. In those cases, additional wind supply replaces production from more expensive sources, leading to a decrease in electricity prices, and thus reduces wind's relative revenue. Nonetheless, it should be noted that these findings are based on the U.S. electricity market, which differs significantly from the European, and particularly Swedish market, in terms of market design, production mix, and transmission constraints. The PJM market uses nodal pricing rather than zonal pricing. As such, the results may have limited generalization for our context. Still, it shows that the literature on relative cannibalization is not entirely conclusive.

More related to our purpose, Stiewe et al. (2025) examine both domestic and cross-border cannibalization effects by analyzing over 30 European bidding zones from 2015 to 2023 using a spatial panel data regression. Their results indicate that a one p.p. increase in domestic wind market share tends to reduce the wind value factor by approximately 0.61 p.p.. They also find that greater interconnectedness increases the flexibility in the European market, which in turn mitigates the cannibalization effect. On the other hand, this same increase in interconnection can also increase cross-border cannibalization. On average the decrease in the cannibalization effect was greater than the increase in a cross-border cannibalization effect (Stiewe et al., 2025). Since the flow-based method is designed to increase the efficiency of cross-border electricity flows, it is expected to have a similar impact to that of increased interconnection.

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[6] See also: Ajanaku and Collins (2023); Peña, Rodríguez, and Mayoral (2022); Stiewe et al. (2025) for further examples

[7] For an example of the definition of the Value Factor, see Clò and D'Adamo (2015) or López Prol, Steininger, and Zilberman (2020).

To the best of our knowledge, no previous study has examined the cannibalization effect in Sweden. However, there is evidence of a merit-order effect in the Swedish electricity market. Findings suggest that increased variable renewable generation, such as wind, tends to lower electricity prices (Jaraitė et al., 2019). The magnitude of this price effect seems to differ between the bidding zones. For example, Sandberg (2024) finds that when wind speed increases by 1 m/s, the electricity price, on average, decreases by 6.4 öre in SE1, 6.7 öre in SE2, 14.6 öre in SE3 and 11.2 öre in SE4. These results are based on time series analysis using separate linear multiple regression models for each zone.

3.3 Hypotheses

3.3.1 Incentives to Invest in Electricity

We hypothesize that incentives to invest in electricity will increase in SE1 and SE2 following the introduction of the flow-based method, due to the expected increase in electricity prices. In contrast, incentives to invest in SE4 are expected to decline. This bidding zone is closely connected to zones with lower prices. Therefore, price convergence in the Nordic region is expected to lead to a lower electricity price in SE4. The expected effect in SE3 is less clear, but based on the simulation results we expect electricity prices, and hence incentives to invest in electricity, to increase in this zone as well.

3.3.2 Relative Incentives to Invest in Wind

We hypothesize that the flow-based method will increase the relative incentives to invest in wind power in SE1 and SE2, which are typically low-price, exporting bidding zones. These zones should experience a relief in the cannibalization effect, as excess supply from high wind output can more easily be exported. In addition, they are unlikely to experience an increased cross-border cannibalization, given their net-exporting position.

In contrast, it is less clear how the relative incentives to invest in wind will change in SE3 and SE4, which are typically importing zones. We hypothesize that incentives to invest in wind power will increase in these zones as well, but likely to a lesser extent. On one hand, increased transmission capacity should reduce the cannibalization effect. On the other hand, these zones may experience a higher cross-border cannibalization effect, as they absorb excess wind supply from other zones. As a result, the net effect on relative incentives to invest in wind following the introduction of the flow-based method is uncertain, but based on previous empirical findings the possible decrease in cannibalization should outweigh the possible increase in cross-border cannibalization.

4 Descriptive Statistics

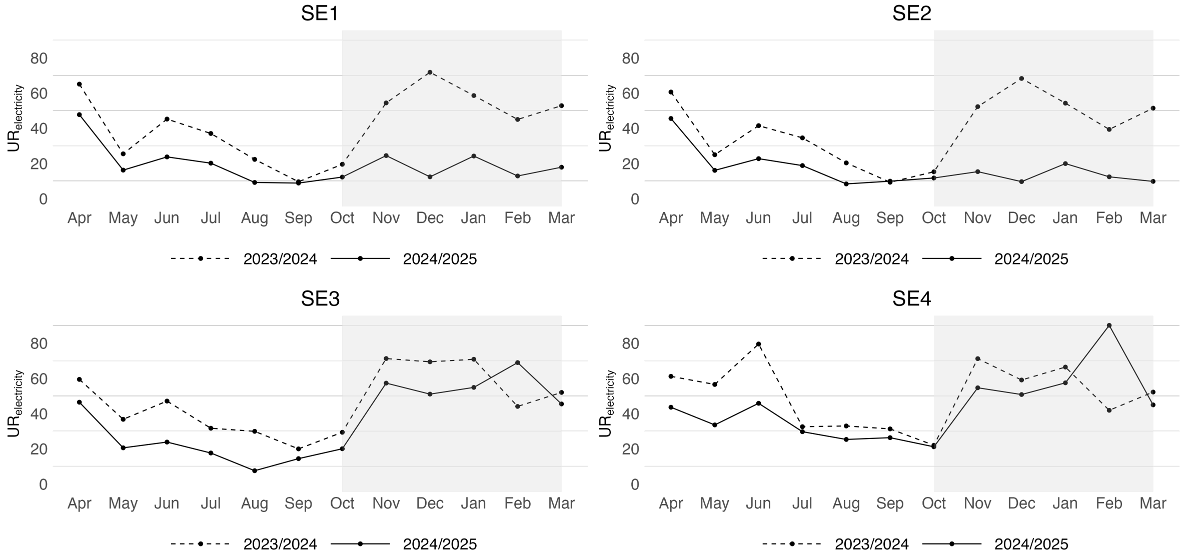
4.1 Incentives to Invest in Electricity

In this section, we present descriptive statistics showing how the introduction of the flow-based method may have affected incentives to invest in electricity, focusing on electricity unit revenue before and after its implementation.

The daily unit revenue of electricity is defined as the average price an electricity producer receives per MWh of electricity produced during a day. That is:

$$\text{UR} = \frac{\sum_{h=1}^{24} p_h q_h}{\sum_{h=1}^{24} q_h}, \tag{1}$$

where p_h is the hourly wholesale electricity price and q_h is the hourly production. To calculate the unit revenue for specific production sources, q_h is replaced with the hourly production from that source.



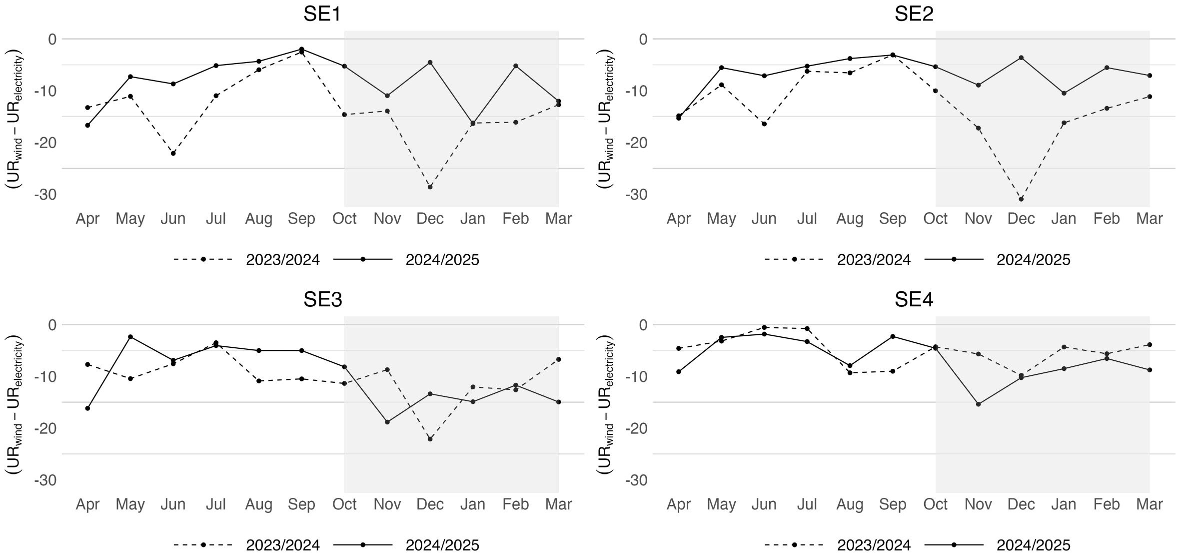
Note: The shaded area represents the period when the flow-based method is introduced. Figure based on data from NordPool (2025).

Figure 5: Comparison of Monthly Average Unit Revenue per Bidding zone

Figure 5 compares each month's average unit revenue with the corresponding month in the previous year to account for seasonal patterns. It shows the average monthly electricity unit revenue across bidding zones, with the shaded area indicating the period with the flow-based method. The 2023/2024 season represents the period under the NTC method, 2024/2025 represents the period under the flow-based method. Contrary to expectations, average electricity unit revenue appears lower in SE1 and SE2 under the flow-based method. This suggests that incentives to invest in these zones have weakened. In SE3 and SE4, there is no clear or consistent difference compared to the same months in the previous year, which also differs from our expectations.

4.2 Relative Incentives to Invest in Wind Power

We also present descriptive statistics on how the flow-based method may have affected relative incentives to invest in wind power. Specifically, we compare the difference between wind unit revenue and electricity unit revenue before and after its implementation.



Note: The shaded area represents the period when the flow-based method is introduced. Figure based on data from NordPool (2025).

Figure 6: Comparison of Difference in Monthly Average Unit Revenue per Bidding zone $[UR_{wind} - UR_{electricity}]$

Figure 6 displays the monthly averages across the two seasons. The absolute difference is negative across all zones, both before and after the introduction of the flow-based method. This aligns with expectations and indicates the presence of a cannibalization effect. In SE1 and SE2, the gap appears to have narrowed following the introduction, suggesting an improvement in the relative investment incentives for wind in these zones. This is consistent with expectations that the cannibalization effect could decrease under the flow-based method. In contrast, the gap seems to have widened in SE4. No clear pattern is observed in SE3.

However, the patterns observed in this section should be interpreted with caution, as incentives to invest in electricity and wind power, may not only be explained by the introduction of a flow-based method. We therefore proceed with an econometric analysis that controls for shifts in supply and demand to better isolate the effect of the flow-based method.

5 Empirical Strategy

We specify two linear regression models to analyze the influence of the flow-based method on incentives to invest in electricity and the relative incentives to invest in wind power to answer our research questions. First, we focus on incentives to invest in electricity. Then, we focus specifically on relative incentives to invest in wind power.

5.1 Variable Selection and Conceptual Motivation: Incentives to Invest in Electricity

5.1.1 Dependent Variable

To answer question (i), we compute the daily unit revenue of electricity, defined as the weighted average price received per MWh by a power plant each day (see Equation 1). This variable is used to capture changes in incentives to invest in electricity across each zone.

5.1.2 Independent variables

We need to control for shifts in supply and demand to ensure that any observed changes in unit revenues are due to the flow-based method, not by variations in market conditions that may coincide with the introduction of the method.

Flow-based Method: We aim to capture the effect of the flow-based method on incentives to invest in electricity by using a dummy variable indicating if the flow-based method has been introduced. It takes the value 1 if the flow-based method is introduced, that is from October 30 2024 and onward, and 0 otherwise.

To make a causal claim regarding the impact of the flow-based method, its introduction must be exogenous to wind and electricity unit revenues, conditional on the included independent variables. The flow-based method was implemented across the entire Nordic region, not just in Sweden, and is also part of a EU regulatory framework. Therefore, this is a reasonable assumption.

We believe this is the most reasonable approach given the available data. One reason is the lack of suitable control groups. The simulated data do not appear to accurately reflect the real market. For example, due to its inability to capture changes in bidding strategies. Cross-country comparisons are also difficult. The Nordic electricity market has a unique structure and power mix across its bidding zones, and the flow-based method may have spillover effect outside of the Nordic region, which make it hard to find unaffected comparison markets.

Supply Side: In Sweden, electricity is mainly produced from five sources: wind, solar, nuclear, hydro and thermal. To control for variation in supply, we include absolute production levels of wind, solar, and nuclear, which we consider as exogenous to price and unit revenue.

Wind and solar generation is exogenous to electricity price in the short run, since its production mainly depends on weather conditions. Additionally, installed capacity of wind power is given in the short run, as the lead time of building a wind power plant is long.[8] The exogeneity assumption for wind power production may fail if, for example, wind power stations would not offer any quantity of electricity at too low prices. This phenomenon is known as curtailment, which is rare in Sweden. One of the largest wind producers in Sweden, Vattenfall (n.d.(b)), reports that almost no curtailment occurs for their wind power stations. Therefore, we believe

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[8] The process from application of building a wind power plant to approval and final construction is around seven to ten years (Vattenfall, n.d.[a])

the exogeneity assumption holds for wind production.[9] We also control for nuclear production. Nuclear is an inflexible dispatchable source, which cannot respond to short-term changes in the market, making the exogeneity assumption likely to hold.

We exclude thermal and hydro production because their output is endogenous to price. These producers adjust their production in response to market prices, therefore including them could bias our estimates. However, excluding them does not lead to omitted variable bias. In short, the equilibrium electricity price depends on demand, exogenous supply, cost parameters and an error term, but not directly on endogenous supply. This is because endogenous production is itself a function of the price. A more detailed, yet simple, example of this is provided in Appendix A.

While hydro power is typically considered endogenous, some parts of hydro production may be exogenous. For example, when hydro reservoirs are relatively full and additional water continues to flow in, production may become less responsive to market signals and can be considered exogenous. As a robustness test, we include water inflow as a proxy for hydro production in an alternative model specification. This variable reflects the potential electricity generation based on the volume of water that flows into reservoirs and hydroelectric stations. However, it is not a perfect measure. For example, if reservoirs are already full, inflowing water may be spilled without producing electricity.

Cross-Border Effects: Given the high level of interconnection in the electricity market, it is important to account for potential cross-border supply effects. Unit revenues may be influenced not only by domestic electricity production, but also by production in neighboring zones. To capture these effects, we include wind power production in neighboring zones in Sweden, as well as nuclear production in SE3, across all bidding zones.

We focus on wind and nuclear production in neighboring zones, because these exogenous sources play a significant role in the power mix, and can more directly influence unit revenues through their effect on supply. In contrast, solar production represents a small share of total electricity production in the region, so solar production in nearby zones is excluded from the analysis.

Demand Side: We control for variations in demand by including several explanatory variables: temperature in the largest city within each zone, time-dummies for the day of the week and week, and the production value index (PVI).[10] Temperature is included because electricity demand tends to vary with it. For example, lower temperatures generally increase demand, as electric heating is common in Swedish households (Sandberg, 2024). The production value index serves as a proxy for industrial electricity consumption, with a lower index indicating reduced production, and thus lower demand. To account for regular demand fluctuation related

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[9] Liebensteiner and Naumann (2022) control for the potential endogeneity issue of wind and solar production by applying an instrumental variable approach, using wind speed to estimate wind power production and sunshine hours to estimate solar production in Germany. They found almost no difference in the results from the instrumental variable approach and the OLS approach, suggesting that endogeneity is not a concern.

[10] Previous studies often use daily electricity consumption as an independent variable to capture variation in demand. This approach requires that demand is perfectly inelastic in the short run. However, electricity demand typically shows some price elasticity (Labandeira, Labeaga, and López-Otero, 2017), and is therefore endogenous.

to seasons, weekdays, and holidays, we include time dummies for both day of the week and week.

For cross-border demand effects, we rely primarily on time dummies and the PVI, which is measured on a national level. We do not include temperature data from neighboring zones, because temperatures across regions are highly correlated. Therefore, it is unlikely to add meaningful variation and might make our estimates less precise. However, since temperatures are similar across zones, we believe that changes in temperature within zones will also reflect changes in demand in neighboring zones to some extent.

5.2 Variable Selection and Conceptual Motivation: Relative Incentives to Invest in Wind Power

To answer question (ii), we calculate the daily unit revenue specifically for wind producers.[11] We focus on the relative incentives to invest in wind power by comparing wind unit revenue to electricity unit revenue. We believe this provides a clear way to evaluate the cannibalization effect and how the flow-based method may affect incentives to invest in wind power.[12]

We control for supply and demand factors that are exogenous to price using the same variables and logic as before. However, because we are specifically interested in how wind production affects wind's relative unit revenue, and how this effect may change under the flow-based method we include an interaction term between the flow-based dummy and wind production within the zone in the second model.[13]

5.3 Regression Specifications

In this section, we present the exact model specifications related to the discussion above. To estimate the effect of the flow-based method on electricity unit revenue and answer research question (i), we specify and estimate Equation 2, referred to as Model 1, for each zone separately using OLS. To answer research question (ii) and determine the change in wind's relative incentives to invest, we estimate Equation 3, referred to as Model 2, also separately for each zone using OLS. This zone-specific approach allows us to identify how the flow-based method affects each zone individually. By estimating one set of coefficients for each bidding zone, we can assess how incentives to invest, both in electricity overall and wind power in relative terms, have changed across the Swedish market after the introduction of the flow-based method.

Model 1: Incentives to Invest in Electricity

$$\begin{aligned}\mathrm{UR}_t^{electricity} = \beta_0 + \beta_1 flowbased_t + \beta_2 wind_t + \delta' wind_{j,t} + \beta_3 solar_t + \beta_4 nuclear_t + \\ + \beta_5 temperature_t + \beta_6 PVI_t + \eta' D_t \ + \mu_t\end{aligned} \tag{2}$$

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[11] We compute the daily wind unit revenue following established literature (López Prol, Steininger, and Zilberman, 2020; Clò and D'Adamo, 2015; Liebensteiner and Naumann, 2022)

[12] Previous studies sometimes use a measure called the wind value factor (see example Section 3.2.2). However, since we have negative observations of both wind unit revenue and electricity unit revenue, we cannot calculate a ratio without adjusting the original data. Because these negative values are not measurement errors, but reflect important real market patterns, we use the difference between the two as a relative measure of incentives to invest in wind power.

[13] We only include an interaction term within the zone due to data limitations; see section 5.4.1 for details

Model 2: Relative Incentives to Invest in Wind

$$\begin{aligned}\mathrm{UR}_t^{wind} - \mathrm{UR}_t^{electricity} = \beta_0 + \beta_1 flowbased_t + \beta_2 wind_t + \beta_3[flowbased_t \cdot wind_t] + \\ \delta' wind_{j,t} + \beta_4 solar_t + \beta_5 nuclear_t + \beta_6 temperature_t + \beta_6 PVI_t + \eta' D_t \ + \mu_t\end{aligned} \tag{3}$$

t represents day. $flowbased_t$ is a dummy variable equal to 1 following the introduction of the flow-based method. $wind_t$ represents daily wind production within the domestic zone. δ' is a row vector of coefficients for wind production in neighboring zones, and $wind_{j,t}$ is a column vector representing wind production in the respective other bidding zones j.[14] $solar_t$ is daily solar production within the bidding zone. $nuclear_t$ is daily nuclear production in SE3.[15] $temperature_t$ captures daily average temperature. PVI_t represents the monthly production value index for Sweden. D_t is a vector of daily and weekly time dummy variables for the day of the week, and week in order to control for working days and holidays, and other seasonal trends. μ_t is a heteroskedasticity and autocorrelation-consistent error term.

In Model 1, the coefficient of interest is β_1, which captures the change in electricity unit revenue after the introduction of the flow-based method, controlling for other confounding factors. In Model 2, the coefficients of interest are β_1, β_2, and β_3. Here, β_1 captures the change in average relative unit revenue of wind after the introduction of the flow-based method, holding other factors constant. β_2 reflects the cannibalization effect, prior to the flow-based method. β_3 captures the change in cannibalization effect after the introduction. Note that these coefficients should be interpreted together to understand the full effect. For example, the relative cannibalization effect after the introduction is given by $\beta_2 + \beta_3$.

5.4 Discussion of Econometric Approach

We believe for our study, that it is best to estimate separate time series models for each bidding zone. This way we can capture zone-specific effects. However, it is important to acknowledge some limitations.

Because bidding zones are interconnected through trade, the error terms may correlate across zones. Prices and production in each zone influence each other, creating interdependencies. As a result, direct comparisons of estimated effects between zones are difficult, as spillover effects may bias the zone-specific coefficients.

We considered using a panel data approach to model all bidding zones together. Ideally, such a model would allow us to explicitly control for both within-zone and cross-zone effects of supply and demand. However, using a standard individual fixed effects model may not be sufficient, as it would be difficult to separate out the individual changes in each zone, which is of interest in our analysis. The standard fixed effect model assumes identical slopes across all bidding zones, but allows for zone-specific intercepts (Verbeek, 2005). One potential solution would be to use one zone as a reference level and then include interaction terms such as with the flow-based

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[14] The bidding zones considered in this analysis are SE1, SE2, SE3 and SE4. As an example, when running the regression for SE1 $j = [SE2, SE3, SE4]$

[15] SE3 is the only bidding zone with nuclear production.

dummy or wind production to allow for different slopes in each zone. However, given the limited number of observations in our dataset, this approach would involve a large number of variables relative to the sample size, which may increase the risk of unreliable estimates. Nevertheless, we expect the results to be similar with those of our current approach.

Another important aspect of using a panel data model would be to account for the simultaneous impact of production and consumption from other zones. This could be addressed by including a spatially weighted matrix based on, for example, interconnection capacity and incorporate this in a spatial lagged panel data model. We do, however, lack data on interconnection capacity between all relevant zones.

Given these challenges and current data limitations, we find that estimating separate time series regressions for each bidding zone is the most suitable approach for our purpose. It offers greater transparency and interpretability, while allowing us to capture zone-specific effects directly. However, we need to keep in mind that error terms may be correlated across zones. As a result, we cannot conclude whether estimated effects differ significantly between zones, which may reduce the efficiency of our estimates.

5.4.1 Threats to Identification

Our model specifications are designed to capture two effects: (i) the impact of the flow-based method on the unit revenue of electricity, and (ii) its effect on the relative incentives to invest in wind power. Both models are estimated using OLS, which focuses on the conditional mean. This means our estimates primarily reflect the average effects of the flow-based method and wind production on unit revenues.

We assume linear relationships between the dependent and independent variables, which allow us to interpret the coefficient estimates as marginal effects. While this assumption may overlook more complex relationships in the data, previous studies have found robust and consistent estimates using similar linear specifications. Given the purpose of our study, we believe OLS is a reasonable and transparent identification strategy. Nonetheless, it is important to acknowledge that more complex relationships may exist, which could be explored in future work using alternative models.

However, there are some potential threats to identification. The validity of our estimates depends on the exogeneity assumption. As previously discussed, we find it reasonable to assume that both wind production and the flow-based method can be treated as exogenous to both electricity and wind unit revenues, conditional on the included control variables.

In Equation 3, we do not account for changes in cross-border effects after the introduction of the flow-based method. For example, we do not include interaction terms between wind production in neighboring zones and the flow-based dummy. This is mainly due to data limitations. We have relatively few observations with the flow-based method, and including additional interaction terms with the flow-based dummy could lead to unreliable results due to multicollinearity. In other words, our sample likely does not contain enough information to accurately estimate these interaction effects (Verbeek, 2005). Excluding this may introduce omitted variable bias.

This bias is likely negative, as cross-border cannibalization can increase under the flow-based method, particularly in importing zones. As a result, our model may underestimate the change in relative incentives to invest in wind power. Therefore, we should interpret our estimates with caution. We still account for supply and demand in the other Swedish zones, but we do not allow for a change in slope after the introduction of the new method. Instead, our main focus is on the change in cannibalization within each zone and the overall incentives to invest in wind power at the zonal level.

Furthermore, non-stationarity is a common challenge in time series data, as it increases the risk of spurious regression results (Wooldridge, 2016). To address this, we test for the presence of a unit root using the Phillip-Perron test. This test is considered to be more robust to heteroskedasticity and autocorrelation, which may be present in our models. This approach is in line with, for example, López Prol, Steininger, and Zilberman (2020) and Ajanaku and Collins (2023). In addition, if serial correlation and/or heteroskedasticity is present, the usual OLS estimator becomes inefficient, and the standard errors will be invalid unless corrected for (Wooldridge, 2016). If serial correlation and heteroskedasticity is found, we compute Newey-West standard errors, which are robust to both heteroscedasticity and autocorrelation (Wooldridge, 2016; Stock and Watson, 2020).

6 Data

6.1 Data Sources

We examine the period from January 1, 2023 to March 31, 2025 across Sweden's four bidding zones. The flow-based method was introduced on October 30 2024, meaning that the data cover five months with the new method. To our knowledge, no shocks to the electricity system occurred during this period. We exclude the year 2022 from our analysis. This year had drastic price changes and volatility, partly driven by external factors such as the war in Ukraine and increased inflation. Therefore, including data from 2022 could lead to more unreliable results.

We use Nord Pool's day-ahead data on hourly wholesale electricity prices, consumption, and electricity production from wind power, solar power, and nuclear power (NordPool, 2025).[16][17]

To account for variations in electricity demand, historical daily temperature data is collected from the Swedish Meterological and Hydrological Institute (SMHI). Data is retrieved for the weather stations closest to the largest city by population in each zone, to capture heating demand (SMHI, 2025). This is Malmö for SE4, Stockholm for SE3, Sundsvall for SE2, and Luleå for SE1. We also use monthly data on production value index (PVI) to proxy the electricity consumption within the industrial sector. Data on PVI are obtained via Statistics Sweden and is aggregated on a national level (Statistics Sweden, 2025b). In 2023, the industry sectors with the highest

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[16] Students can get access to historical data from Nord Pool without cost.

[17] Due to data accessibility and the expectation of similar outcome, we use realized data instead of forecasted data for electricity production. While this may introduce some bias, there is almost perfect correlation between day-ahead forecasts and actual values (López Prol, Steininger, and Zilberman, 2020; Liebensteiner and Naumann, 2022), suggesting that any such bias is likely small.

electricity consumption in Sweden was the pulp and paper industry, followed by the steel and metal industry, and the industries for metal goods, machinery, electrical and optical equipment, and transport. These three sectors accounted for approximately 80% of the total electricity consumption in the industrial sector (Swedish Energy Agency, 2025). Due to the data structure on Statistics Sweden, we collect data on PVI from these three sectors, and use their average as our final measure. As this data is aggregated on a monthly basis, it gives us little variation on a daily basis. This is, however, likely the most efficient way of controlling for variation in demand in combination with time dummy variables and temperature, given the available data.

6.2 Summary Statistics

Table 1 presents summary statistics for the entire period, covering 821 observations per zone. Negative prices and unit revenues occur in all zones during this period. On average, SE4 has the highest electricity unit revenue, followed by SE3. SE1 and SE2 have lower and more similar values. These patterns are also observed for wind unit revenue. Additionally, the standard deviation for wind production is large relative to the mean across all zones, indicating that it varied a lot from day to day.

Bidding zones that mainly export electricity (SE1 and SE2) tend to have higher electricity unit revenues than the average price. In contrast, the importing zone (SE4) typically has a lower unit revenue than the average price. SE3, which has a more balanced trade pattern shows almost no difference between the two. This suggest that producers in exports zones are better at capturing the market price, while producers in importing zones benefit less from high prices. Therefore, using the average price as a measure of producers' average revenue in a zone could be misleading.

7 Results and Analysis

7.1 Regression Results: Incentives to Invest in Electricity

Figure 7 shows the estimated electricity unit revenue before and after the introduction of the flow-based method, based on Model 1. It shows that on average, and controlling for supply and demand, electricity unit revenue is lower in SE1 and SE2 after the introduction of the flow-based method. Specifically, the results indicates that, on average, the flow-based method decreased daily electricity unit revenue by approximately 21.44 EUR/MWh in SE1 and 22.89 EUR/MWh in SE2. No significant effect is observed in SE3 and SE4. These results mirror the patterns in Figure 5. This indicates that incentives to invest in electricity have declined in SE1 and SE2 under the flow-based method, while remaining largely unchanged in SE3 and SE4.

Table 1: Summary Statistics

Variable	Min	Median	Mean	Max	Std. Dev.
SE1					
Wind Production (GWh)	0.35	15.613	19.112	61.076	14.252
Solar Production (GWh)	0	0.007	0.016	0.8	0.2
Daily Consumption (GWh)	17.852	30.341	30.425	46.755	6
$Unit\ Revenue_{wind}$	−8.707	20.596	28.778	146.337	27.109
$Unit\ Revenue_{electricity}$	−7.385	23.478	31.676	184.470	29.057
Daily Price (Euro)	−8.309	22.180	30.655	187.361	28.750
Temperature	−33.800	1.242	2.451	22.046	10.630
SE2					
Wind Production (GWh)	1.736	37.460	43.594	134.039	29.643
Solar Production (GWh)	0	0.91	0.147	0.672	0.155
Daily Consumption (GWh)	22.022	41.960	42.511	92.987	10.019
$Unit\ Revenue_{wind}$	−5.189	20.810	28.402	186.929	27.600
$Unit\ Revenue_{electricity}$	−4.985	22.734	30.970	200.563	29.349
Daily Price (Euro)	−8.309	22.586	30.375	189.303	28.922
Temperature	−25.158	2.417	3.855	20.329	9.236
SE3					
Wind Production (GWh)	1.747	23.011	27.044	78.651	17.794
Solar Production (GWh)	0.01	1.579	2.330	8.900	2.333
Nuclear Production (GWh)	65.79	137.31	132.43	168.70	22.01
Daily Consumption (GWh)	146.823	231.871	233.064	365.201	46.9
$Unit\ Revenue_{wind}$	−7.699	32.568	42.618	208.206	35.819
$Unit\ Revenue_{electricity}$	−8.535	35.339	45.233	215.019	37.017
Daily Price (Euro)	−8.309	35.174	45.097	211.770	36.760
Temperature	−12.450	6.188	7.634	23.292	7.993
SE4					
Wind Production (GWh)	0.712	13.546	15.919	47.387	10.685
Solar Production (GWh)	0.006	1.231	1.624	5.576	1.522
Daily Consumption (GWh)	37.484	60.359	61.167	98.914	12.861
$Unit\ Revenue_{wind}$	−9.568	48.756	55.458	346.346	40.115
$Unit\ Revenue_{electricity}$	−11.524	49.354	56.845	338.645	40.985
Daily Price (Euro)	−8.309	54.110	58.729	309.972	40.554
Temperature	−10.150	7.700	8.936	24.200	6.966
Common					
PVI	95.125	100.850	100.901	107.475	2.691

Note: Unit revenue is measured in EUR/MWh.

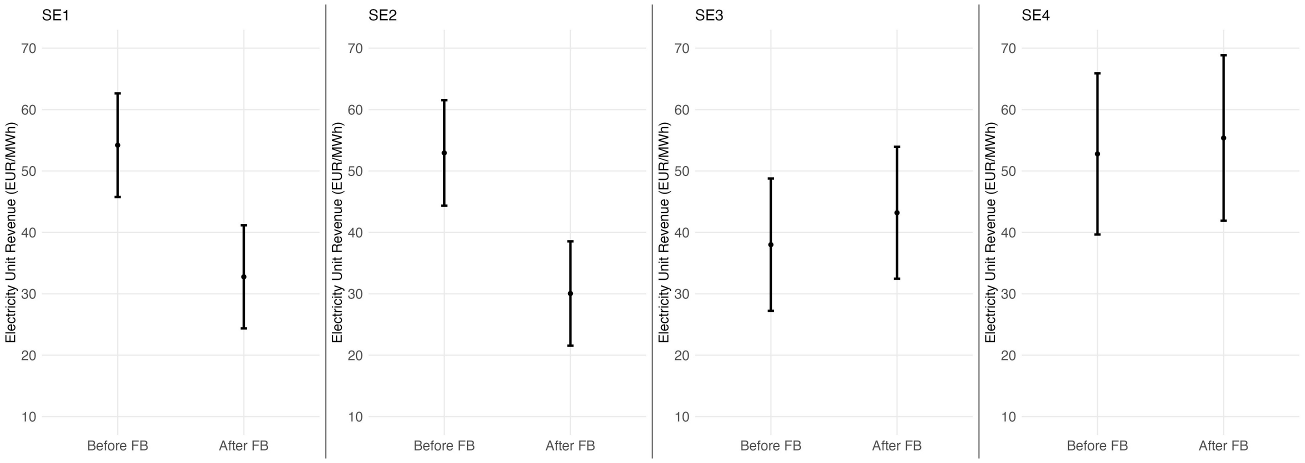

Figure 7: Estimated Electricity Unit Revenue per Bidding Zone (with 95% Confidence Interval)

The full regression results are provided in Table 2.[18] We do not focus on interpreting the coefficients of the control variables, as their signs are mostly in line with theory and expectations, giving us more confidence in the model specification. However, for completeness, we briefly discuss these results.

The results provide support for the presence of a cannibalization effect, where higher wind production within a bidding zone is associated with a decrease in electricity unit revenue in that same zone. There is also evidence of cross-border cannibalization, where increased wind generation in neighboring zones is linked to a decrease in electricity unit revenue in the domestic zone. No significant effect is found for solar production. This is likely due to its relatively small share in total production. As it contributes only marginally to overall supply, its influence on average electricity revenue is expected to be limited.[19] Nuclear production shows a consistently negative relationship with electricity unit revenue across all bidding zones, which aligns with expectations.

Regarding demand dynamics, a negative relationship between temperature and unit revenue is observed across all zones. This is in line with expectations, as higher temperatures typically reduce demand, which in turn lowers electricity prices and unit revenue. The coefficient on the production value index (PVI) is positive and statistical significant in all zones expect SE4. A higher PVI indicates increased production, and, consequently, higher demand, which is expected to increase unit revenue. Lastly, we control for week and weekday effects. As expected, demand is typically higher on weekdays, resulting in higher unit revenue compared to weekends.

As a robustness test, we also estimated Model 1 including water inflows into hydro reservoirs

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[18] Before running the regression, we conducted a Phillips-Perron test for stationarity. The results indicate that the null hypothesis of a unit root can be rejected at the 5% significance level, suggesting that the series is stationary (see Table B3 for more details). We also conducted a Breusch-Godfrey and Breusch-Pagan test and determined that serial correlation and heteroscedasticity may be present, therefore Newey West standard errors with varying lags were implemented.

[19] The estimated coefficient for solar in SE1 may seem odd, but given the large standard errors, we do not draw any conclusions from this. The result likely reflects the low and variable solar output in SE1, which ranges from zero to a maximum of 0.8 GWh per day. It is also possible that days with higher solar production coincided with warm, sunny days, which increased demand. This could cause some confounding effects, even though we control for temperature.

Table 2: Regression Results - Model 1

	Dependent Variable: Electricity Unit Revenue			
	SE1	SE2	SE3	SE4
	(1)	(2)	(3)	(4)
$flowbased$	-21.441^{***}	-22.896^{***}	5.201	2.595
	(2.838)	(2.703)	(3.643)	(5.029)
Supply				
$wind_{SE1}$	-0.266^{***}	-0.342^{***}	-0.272^{***}	-0.104
	(0.067)	(0.063)	(0.070)	(0.108)
$wind_{SE2}$	-0.306^{***}	-0.300^{***}	-0.145^{***}	-0.157^{***}
	(0.036)	(0.037)	(0.037)	(0.055)
$wind_{SE3}$	-0.185^{**}	-0.131^{*}	-0.345^{***}	-0.275^{**}
	(0.076)	(0.074)	(0.085)	(0.130)
$wind_{SE4}$	-0.252^{**}	-0.286^{**}	-0.894^{***}	-1.483^{***}
	(0.115)	(0.116)	(0.129)	(0.214)
$solar_i$	-24.850	5.060	0.701	0.226
	(59.003)	(9.510)	(0.834)	(1.282)
$nuclear_{SE3}$	-0.091^{*}	-0.088^{*}	-0.333^{***}	-0.339^{***}
	(0.053)	(0.053)	(0.088)	(0.108)
Demand				
$temperature_i$	-0.570^{***}	-0.965^{***}	-3.269^{***}	-3.024^{***}
	(0.167)	(0.224)	(0.363)	(0.497)
pvi	1.470^{***}	1.446^{***}	1.364^{***}	0.746
	(0.334)	(0.341)	(0.405)	(0.552)
$Monday$	11.024^{***}	11.019^{***}	21.739^{***}	27.277^{***}
	(1.429)	(1.494)	(1.876)	(2.182)
$Tuesday$	11.510^{***}	12.101^{***}	21.305^{***}	29.277^{***}
	(1.643)	(1.741)	(2.130)	(2.621)
$Wednesday$	11.889^{***}	12.759^{***}	23.270^{***}	30.191^{***}
	(1.591)	(1.637)	(2.383)	(2.862)
$Thursday$	12.174^{***}	12.423^{***}	22.526^{***}	28.882^{***}
	(1.720)	(1.812)	(2.320)	(2.821)
$Friday$	9.207^{***}	9.357^{***}	17.621^{***}	22.580^{***}
	(1.649)	(1.832)	(2.116)	(2.182)
$Saturday$	2.355^{**}	2.718^{***}	2.992^{**}	3.332^{**}
	(0.957)	(1.040)	(1.417)	(1.583)
$Constant$	-52.789	-50.586	2.857	88.947
	(38.773)	(39.787)	(46.251)	(59.295)
Week Dummies	Yes	Yes	Yes	Yes
Observations	821	821	821	821
Adj. R2	0.766	0.769	0.76	0.663

Note: *p<0.1; **p<0.05; ***p<0.01

Heteroscedasticity- and autocorrelation-consistent (Newey-West) standard errors in parentheses.

in each zone as additional control variables. The results for the flow-based method remained relatively robust (see Table B1). The full model specification is provided in Equation 5 in Appendix B. However, it should be noted that according to the Phillips-Perron test, water inflow is only stationary at the 90% confidence level in SE1 and SE4.

7.2 Regression Results: Relative Incentives to Invest in Wind Power

The results of Model 2 are presented in Table B2 in Appendix B.[20] The coefficient for wind production within the same zone is positive and statistically significant at the 5% level across all bidding zones. This contradicts theoretical expectations of a cannibalization effect. A positive relationship implies that increased wind production raises wind's relative unit revenue. This discrepancy points to a possible model misspecification or omitted variable bias.

One potential source of misspecification is how wind production is distributed throughout the day. As shown in Figure 8, the daily pattern of wind production can vary depending on total wind output that day. On very windy days, wind production tends to be high also around midday and the afternoon. This suggests that the timing of production, not only its volume, affects revenue. Our original model may therefore capture two effects in the wind production variable. Both a cannibalization effect, where increased supply lowers prices, and a timing effect, where better alignment between wind production and high demand improves wind revenue. This could help explain the unexpected positive coefficient for wind production.

To account for this, we analyze the intraday patterns of wind production using Figure 8. The figure shows a dip in wind output around 12:00 and higher production during the early morning and nighttime hours, except in the highest wind quartile. To quantify this pattern, we compare wind production at 12:00 and 00:00 for each day and standardize the difference by that day's average wind production. This measure captures whether production is concentrated around the middle of the day or during the night and is defined in Equation 4.

$$distribution_t^{wind} = \frac{q_{h=12:00}^{wind} - q_{h=00:00}^{wind}}{\bar{q_t^{wind}}}, \tag{4}$$

where $\bar{q^{wind}}$ represents the average hourly wind production for day t, $q_{h=12:00}^{wind}$ is the wind production at 12:00 and $q_{h=00:00}^{wind}$ is the wind production at 00:00. The resulting variable reflects the normalized difference between midday and nighttime wind production. It is designed to capture daily variation in the timing of wind production, rather than its absolute level. A positive value indicate that wind production is higher at midday (as seen in the highest wind quartile), while a negative value suggests that more wind power is produced during the night.

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[20] Before running the regression, we conducted a Phillips-Perron test for stationarity. The results indicate that the null hypothesis of a unit root can be rejected at the 5% significance level, suggesting that the series is stationary (see Table B3 for more details). We also conducted a Breusch-Godfrey and Breusch-Pagan test and determined that serial correlation and heteroscedasticity may be present, therefore Newey West standard errors with varying lags were implemented.

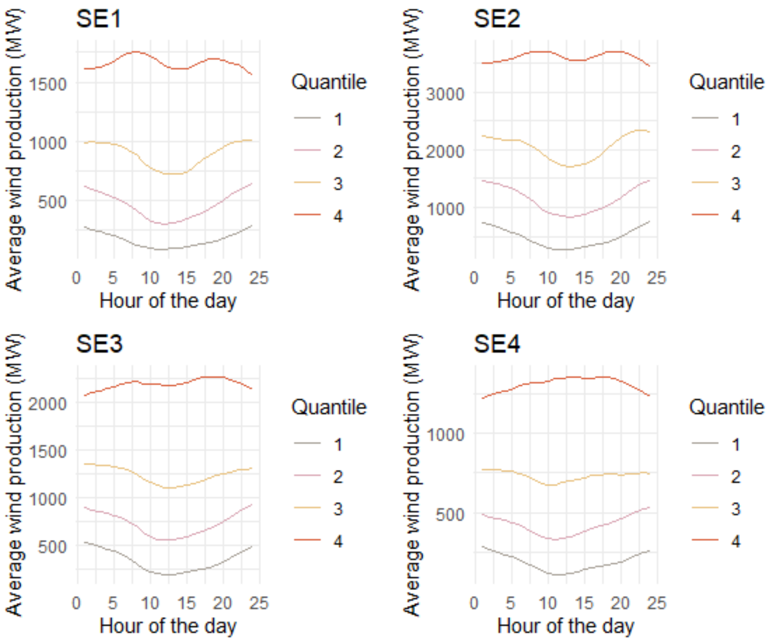

Figure 8: Intraday Wind Production Patterns by Bidding Zone and Wind Production Quartile

This measure provides an imperfect, yet useful, proxy for the daily pattern of wind production. By including it, we can better distinguish between two effects: (i) the direct effect of wind production on relative wind unit revenue (i.e. the cannibalization effect) and (ii) the timing effect of wind production on wind relative unit revenue. To account for this, we extend Model 2 by including this new variable. The updated model specification is provided in Equation 6 in Appendix B, and the results are presented in Table 3 .

When we control for the timing of production, the results change. The previously significant positive effect of wind production is no longer statistically significant at the 5% level. In SE1 and SE4, the estimates become statistically insignificant. In SE2, the estimate remains positive but is only statistically significant at the 10% level. In SE4, the coefficient turns negative but is only statistically significant at the 10% level. While these results still do not provide clear support for a cannibalization effect, they align more with expectations. The positive coefficient for the distribution variable supports our belief that the timing of wind production impacts relative revenue. As the distribution measure increases, meaning more wind production also during midday, wind performs better relative to the market. Given that wind unit revenue is typically lower than the average electricity revenue, this finding suggests a narrower gap and improved relative performance for wind on such days.

Having accounted for the timing effect, we now turn to the main variables of interest: the flow-based method and its interaction with wind production. The results for both the flow-based dummy and its interaction with wind production remain relatively robust across both models. The estimated coefficients for the interaction term between wind production and the flow-based dummy are positive across all zones, but only statistically significant in SE2 and SE4. This suggests that the cannibalization effect has decreased in these zones following the introduction of the flow-based method. However, since the estimates related to wind production is not

Table 3: Regression Results - Model 3. Accounting for intraday wind distribution.

	Dependent Variable: $UR_{wind} - UR_{electricity}$			
	SE1	SE2	SE3	SE4
	(1)	(2)	(3)	(4)
$flowbased$	−1.706	−4.151***	−0.371	−4.064***
	(1.609)	(1.495)	(0.875)	(1.323)
$(flowbased \cdot wind_i)$	0.060	0.068***	0.017	0.157***
	(0.040)	(0.018)	(0.017)	(0.046)
Supply				
$wind_{SE1}$	0.014	0.018	−0.011	−0.012
	(0.022)	(0.013)	(0.016)	(0.021)
$wind_{SE2}$	0.014	0.014*	0.011	0.001
	(0.010)	(0.008)	(0.008)	(0.011)
$wind_{SE3}$	0.050**	0.025	−0.034*	−0.010
	(0.021)	(0.016)	(0.018)	(0.019)
$wind_{SE4}$	−0.018	−0.003	0.092***	−0.022
	(0.031)	(0.025)	(0.024)	(0.030)
$distribution_i^{wind}$	1.128***	1.417***	2.886***	2.757***
	(0.249)	(0.242)	(0.314)	(0.378)
$solar_i$	10.888	2.580*	0.434***	1.052***
	(10.102)	(1.499)	(0.119)	(0.308)
$nuclear_{SE3}$	0.019	0.021*	0.046***	0.035**
	(0.015)	(0.011)	(0.010)	(0.014)
Demand				
$temperature_i$	0.057	0.012	0.126***	0.135**
	(0.049)	(0.042)	(0.047)	(0.058)
pvi	−0.007	0.000	−0.024	−0.092
	(0.076)	(0.058)	(0.066)	(0.075)
Constant	−7.999	−10.261	−7.638	2.670
	(8.989)	(6.877)	(6.893)	(7.594)
Weekday Dummies	Yes	Yes	Yes	Yes
Week Dummies	Yes	Yes	Yes	Yes
Observations	821	821	821	821
Adj. R2	0.196	0.271	0.322	0.336

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Heteroscedasticity- and autocorrelation-consistent (Newey-West) standard errors in parentheses.

statistically significant (at the 5% level) and we have an imperfect quantification of distribution patterns, the exact size of the cannibalization effect is not possible to conclude.

The coefficients for the flow-based dummy variable are negative across all zones, but only statistically significant in SE2 and SE4. This coefficient should be interpreted together with the interaction term to understand the effect of the flow-based method on relative incentives to invest in wind power. To estimate the change in relative unit revenue at the average wind production, we combine the effect of the flow-based dummy with the interaction term, evaluated at the average wind production during the flow-based period.[21] The final estimates are presented in Table 4.

In SE1, wind producers earn approximately 0.132 EUR more per MWh produced relative to the market under the flow-based method compared to the NTC method. However, this estimate is based on statistically insignificant coefficients, so no effect can be concluded. In SE2, wind power

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[21] Specifically, we compute $\beta_1 + \beta_3 \cdot \bar{wind}$ based on Equation 6, where $\bar{wind}$ is the average wind production under the flow-based method.

Table 4: Estimated Change in Relative Wind Unit Revenue Under the Flow-Based Method

Zone	**Average Wind Production(GWh)**	**Change in Relative Wind Unit Revenue (EUR/MWh)**
SE1	30.64	0.132
SE2	63.37	0.158
SE3	35.54	0.233
SE4	18.02	-1.235

Note: Estimates are based on the coefficients reported in Table 3 and the average wind production during the flow-based period.

stations earn around 0.158 EUR more per MW relative to the market under the flow-based method. This estimate is based on statistically significant coefficients, suggesting a positive effect of the flow-based method on relative incentives to invest in wind power. In SE3, both the flow-based dummy and its interaction with wind production are statistically insignificant, so no effect can be concluded. However, the point estimates suggest that wind producers may be relatively better off after the introduction. Lastly, in SE4, the estimated effect is negative. Wind power producers experience a decrease of about 1.235 EUR per MWh relative to market. This is based on statistically significant coefficients and indicates that wind power performs worse relative to the market under the new method. These results are mainly consistent with the patterns observed in Figure 6. To summarize, wind producers tend to perform relatively better after the introduction of the flow-based method in SE2, relatively worse in SE4, while no significant effects emerge in SE1 and SE3.

The additional control variables are not the primary focus of this study, but we will briefly discuss them for completeness. The estimates are somewhat consistent with previous findings. Results from Model 1 shows that our independent variables seem to explain much of the variation in electricity unit revenue. This gives us confidence that they are reasonable control variables. But, the effects differ when investigating the relative wind unit revenue, which is to be expected. We observe a positive and statistically significant relationship at the 5% level between solar production and relative wind unit revenue in SE3 and SE4. This aligns with the findings of López Prol, Steininger, and Zilberman (2020). It suggests that solar production impacts the average unit revenue of electricity more strongly than the average unit revenue of wind. In other words, when daily solar production increases, wind experience a lower revenue decline on average compared to the overall market. It is possible that the effect is more evident in SE3 and SE4, which has a larger share of solar power in their production mix compared to SE1 and SE2. We also find a positive relationship between nuclear production and the relative wind unit revenue. This suggests that a higher nuclear production affects the wind's average unit revenue less than the electricity unit revenue as a whole. Regarding demand, estimates for the production value index are statistically insignificant across all zones, so we cannot say much about its effect. However, we find that higher temperatures are associated with an increase in wind's relative unit revenue in SE3 and SE4. Since higher temperatures typically reduce demand, which in turn tends to lower prices, this suggests that shifts in demand influence overall electricity unit revenue more than wind powers unit revenue.

8 Discussion

8.1 Incentives to Invest in Electricity

Sweden aims to expand its domestic electricity production to meet increasing future demand. To achieve this, it is important to support incentives to invest in electricity production, and the flow-based method could influence where it is most profitable to invest.

Our descriptive statistics show that electricity unit revenue decreased in SE1 and SE2 after the introduction of the flow-based method, while no clear patterns emerged in SE3 and SE4. These conclusions were confirmed in the econometric analysis, which accounted for changes in supply and demand, both when including and excluding water inflows into hydro stations. These findings are somewhat surprising, as we expected that the flow-based method would increase incentives to invest in SE1 and SE2, as these zones typically have lower prices compared to their neighbors. This expectation was also supported by simulation results conducted by the responsible Nordic transmission system operators. This would have promoted expansion of electricity production in the north, where demand is also expected to increase significantly.

Instead, the results indicate that the flow-based method, despite being viewed as a standard in EU, has not increased incentives to invest in the north of Sweden as first thought. However, other patterns may appear in the long run, as power system operators gain more experience in navigating this new market.

8.2 Relative Incentives to Invest in Wind Power

We pay special attention to how the flow-based method has affected incentives to invest in wind power. This focus is relevant as wind power is expected to play a key role in meeting future electricity demand. In addition, the flow-based method is argued to better integrate renewable energy sources into the electricity market.

On average, wind unit revenue remains lower than overall electricity unit revenue across all zones, regardless of capacity calculation method. Our descriptive statistics indicate that the flow-based method appears to improve relative incentives to invest in wind in SE1 and SE2, reduce them in SE4, while no change is observed in SE3. The econometric analysis partly confirms these findings. At average wind production levels relative incentives to invest in wind power seem to be higher in SE2 and lower in SE4 under the flow-based method. No significant effects are observed in either SE1 or SE3.

Theory and previous research suggest that the relative incentives to invest in wind power can improve with increased transmission capacity, but only if the reduction in the cannibalization effect outweighs the increase in cross-border cannibalization effect. Based on this, we expected an increase in relative incentives to invest in wind across all zones following the introduction of the flow-based method, where the effect was expected to be larger in SE1 and SE2 compared to SE3 and SE4. Our results support this hypothesis for SE2, but no significant effect was observed in SE1 or SE3. SE2 is an exporting zone with a large share of Sweden's wind power. Increased cross-border transmission capacity under the flow-based method appears to have allowed SE2 to export surplus wind production more effectively, reducing local price-suppressing effects caused by excess supply. In contrast, SE4 experienced a decrease in relative incentives to invest in wind power. SE4 typically imports electricity, so it is likely more exposed to cross-border cannibalization than SE2. This may explain the observed decline.

8.2.1 The Cannibalization Effect

Since wind unit revenue is, on average, lower than electricity unit revenue across all zones, this suggest that the cannibalization effect is present. It shows that wind producers tend to earn less than the market average.

When we tried to quantify the cannibalization effect, our original model showed a positive relationship between wind production and wind's relative unit revenue. This implies that higher wind production is associated with an increase in wind's relative unit revenue, which contradicts the theoretical concept of a cannibalization effect. We located this counterintuitive finding to the intraday distribution of wind production. On high-wind days, wind production tends to be high also during midday and afternoon, when demand also tend to be higher. Thereby, improving wind's relative revenue on such days. This could explain the positive estimate.

Our refined analysis does not provide clear evidence of a cannibalization effect. The estimated relationship between wind production on wind's relative unit revenue is inconclusive. On average, the effect appears to be close to zero across all bidding zones. Wind production affects both wind unit revenue and the overall electricity unit revenue in similar ways, making the relative difference small. Sweden has a relatively large share of wind power in their production mix. This can reduce the relative difference between wind unit revenue and average electricity unit revenue. As a result, the cannibalization effect may be smaller in Swedish bidding zones compared to markets with lower wind shares, which have primarily been studied in previous research. Nonetheless, we avoid drawing any conclusions about the cannibalization effect, given the potential limitations in our analysis.

8.3 Limitations and Future Research

Our models only account for supply and demand in the Swedish bidding zones and not in neighboring countries. This may introduce omitted variable bias, since production and consumption from neighboring countries can influence electricity prices in the local zone and our estimates. Specifically, the models do not capture potential changes in the cross-border cannibalization effect after the introduction of the flow-based method. If this effect has increased, as is likely, it could lower unit revenues, especially in importing zones. Since this downward pressure on local prices is not captured, it may lead to a negative bias, meaning we underestimate the impact on incentives to invest. We are unable to account for changes in the cross-border cannibalization effect following the introduction of the flow-based method, as limited data availability prevent us from including interaction terms between the flow-based dummy and supply variables in all neighboring zones. Therefore, we encourage future research once more data under the flow-based method become available. We also recommend that future studies include data from all Nordic bidding zones to allow for a more comprehensive analysis.

A second limitation is that the current dataset with realized data includes five months with the flow-based method, mainly ranging over the winter season. Future research should consider a longer time period, including all seasons, to better assess the long-term effects of the flow-based method. Third, the error terms across zones may be correlated, meaning that coefficients should be compared with great caution between bidding zones. Fourth, in our analysis we assume that the flow-based method primarily increases flows from low-price to high-price zones. But, as noted in the background section, the method can also lead to non-intuitive flows, where electricity flows in the opposite direction. While these flows could affect markets outcomes, we expect their overall impact to be limited. However, in future research the potential impact of non-intuitive flows should be considered.

Lastly, while our attempt to quantify the effect of timing of production is imperfect, it highlights an important avenue for future research. Moreover, it is unclear if the flow-based method change the effect of distributional patterns on wind's relative unit revenue. This is outside of the scope of this paper, so we do not control for it, but we encourage future research to investigate this further.

8.4 Policy Implications

This paper investigates how the flow-based capacity calculation method has influenced incentives to invest in electricity, both in general and for wind power specifically, across Sweden's bidding zones. This is important as Sweden's electricity production must expand to support a growing demand, with wind power expected to play an important role.

This study finds no evidence that the flow-based method increases incentives to invest in electricity in any of Swedish bidding zone. Instead, incentives appear to have declined in SE1 and SE2. This may reduce future expansion. Focusing specifically on wind power, which typically has a comparative disadvantage compared to other sources due to the cannibalization effect, we find suggestive evidence that the relative incentives to invest in wind power have improved under the flow-based method in SE2. In contrast, the disadvantage appears to have increased in SE4. These results suggest that the flow-based method may only support the expansion of wind power in certain regions.

Our findings may also be relevant to the ongoing political debate regarding whether the division into bidding zones in the Swedish electricity market is fair, due to large price differences between the northern and southern zones. So far, the flow-based method appears to have had unexpected effects in the Swedish context. We do not observe the expected price increases in SE1, SE2 or SE3, instead prices seem to have declined in SE1 and SE2. Although, this was not our main focus, our results imply that the regional price differences between northern and southern Sweden may have increased further during the initial period with the flow-based method.

Finally, the flow-based method is highly complex and limited understanding among participants may have contributed to the unexpected outcomes we observe. One potential policy measure is to increase transparency around its mechanisms and calculation results. This could reduce uncertainty and help market participants to better evaluate and adjust their bids.

9 Conclusions

Sweden needs to expand its electricity production to meet future demand, driven by factors such as electrification. Wind power is expected to play a key role in this expansion. Recently, the Nordic countries implemented the flow-based capacity calculation method, which influences bidding zones electricity prices by determining how much transmission capacity is available. The method is assumed to lead to price convergence in the Nordic region, which may in turn impact where it is most profitable to invest in electricity production in Sweden. It may also help reduce the cannibalization effect, which could improve incentives to invest in wind.

Contrary to expectations, we found that incentives to invest in electricity declined in SE1 and SE2 after the introduction of the flow-based method, while no significant effect appeared in SE3 and SE4. This may reduce future expansion of electricity production overall, but especially in the north, an area where demand is expected to grow significantly. When focusing specifically on incentives to invest in wind power, wind producers typically earn less than the market average, likely due to the cannibalization effect. Notably, this disadvantage appears to have decreased in SE2 following the implementation of the flow-based method. The opposite effect is observed in SE4. This suggests that SE2 has become a more suitable market for wind production, while SE4 has become less suitable.

Given the limited time period since the introduction of the flow-based method and the lack of data from neighboring countries in this study, these findings should be interpreted with caution. To gain a more comprehensive understanding of its impacts, future research should incorporate additional data as it becomes available, both from Sweden and neighboring bidding zones. Furthermore, this study finds that the timing of wind production, not just its total volume, affects the daily relative revenue of wind power. This highlights an interesting avenue for future research to better understand the underlying mechanisms of the cannibalization effect.

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Appendix A: Example - Solving for Equilibrium Price

We exclude endogenous supply from our model specifications. We argue that this does not introduce omitted variable bias.

To illustrate this more clearly, consider a simple setting with only one bidding zone which has no transmission lines to other zones. In this case, the total supply in Zone 1 is the sum of exogenous supply, such as wind power (denoted Q_1) and endogenous supply, such as hydro and thermal (denoted X_1). Total supply in Zone 1 is then given by: $S_1 = Q_1 + X_1$.

Endogenous supply is price-sensitive and determined by the marginal cost of production. Assuming a linear marginal cost curve, the inverse supply function for X_1 can be written as:

$$\mathrm{Price}_1 = \gamma_1 + \delta_1 X_1 + \mu_1$$

where γ_1 is the baseline marginal cost, $\delta_1 > 0$ is the slope of the marginal cost curve and μ_1 is an error term. Solving for X_1 gives:

$$\mathrm{X}_1 = \frac{(Price_1 - \gamma_1 - \mu_1)}{\delta_1}$$

This shows that endogenous supply is a function of the electricity price and cost parameters. If the price increase, more endogenous supply becomes available.

To clear the market, supply must equal demand ($S_1 = D_1$). For simplicity, we assume that demand (D_1) is perfectly inelastic, meaning it is independent of price. Substituting in the expression for X_1 into the market-clearing condition gives:

$$\mathrm{S}_1 = Q_1 + X_1 = Q_1 + \frac{(Price_1 - \gamma_1 - \mu_1)}{\delta_1} = D_1$$

Solving for the equilibrium price yields:

$$\mathrm{Price}_1 = (D_1 - Q_1)\delta_1 + \gamma_1 + \mu_1$$

This equation shows that the equilibrium price depends on demand, exogenous supply, cost parameters and the error term, but not directly on endogenous supply. Since endogenous production is itself a function of price, excluding it from the model does not introduce omitted variable bias.

Appendix B: Supplementary Results

B.1. Incentives to Invest in Electricity

As a robustness test we include a proxy variable for hydro production in an alternative model specification of Model 1. We use water inflow, which reflects the potential hydro electricity production based on the volume of water that flows into reservoirs and hydroelectric stations. Most of the water flowing into hydro power stations are used to generate electricity directly (Johanneson and Sjöbohm, 2018). Since water flows mainly depends on weather conditions, such as rain or melting snow, this variable is believed to capture the exogenous part of hydro production.[22] The updated model is defined in Equation 5.

$$\begin{aligned}\text{UR}_t^{electricity} &= \beta_0 + \beta_1 flowbased_t + \beta_2 wind_t + \delta' wind_{j,t} + \beta_3 solar_t + \beta_4 hydro_t + \gamma' hydro_{j,t} + \\ &\quad \beta_5 nuclear_t + \beta_6 temperature_t + \beta_7 PVI_t + \eta' D_t \ + \mu_t \end{aligned} \tag{5}$$

The results from estimating this equation are presented in Table B1. Overall, the estimates remain relatively robust compared to Model 1. However, the results related to hydro production are mixed across zones. Typically, we would expect a negative relationship between hydro production and electricity unit revenue within the same zone, which is also observed in SE3 and SE4. In contrast, the estimated relationship is positive in SE1, contradicting theoretical expectations. This suggest that our proxy variable for hydro production may not fully capture its true impact on the market. Still, given data limitations and endogeneity concerns when including hydro production directly, we believe this is the most appropriate proxy available.[23].

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[22] Data on water flow on a weekly level for each bidding zone can be retrieved by contacting Energiföretagen Sverige.

[23] The Phillips-Perron test reject the null hypothesis of the presence of a unit root only at the 10% level for hydro in SE1 and SE4. There is also a high correlation between hydro in SE1 and SE2. Therefore, these regression results should be interpreted with caution

Table B1: Regression Results - Extension of Model 1, Including Hydro Production

	Dependent Variable: Electricity Unit Revenue			
	SE1	SE2	SE3	SE4
	(1)	(2)	(3)	(4)
$flowbased$	-23.826^{***}	-25.379^{***}	1.459	-2.800
	(3.543)	(3.445)	(3.576)	(4.928)
Supply				
$wind_{SE1}$	-0.279^{***}	-0.349^{***}	-0.285^{***}	-0.133
	(0.073)	(0.066)	(0.071)	(0.114)
$wind_{SE2}$	-0.313^{***}	-0.309^{***}	-0.153^{***}	-0.163^{***}
	(0.036)	(0.038)	(0.038)	(0.052)
$wind_{SE3}$	-0.193^{**}	-0.141^{*}	-0.365^{***}	-0.296^{**}
	(0.080)	(0.075)	(0.083)	(0.124)
$wind_{SE4}$	-0.243^{**}	-0.272^{**}	-0.876^{***}	-1.467^{***}
	(0.118)	(0.117)	(0.132)	(0.199)
$solar_i$	-44.663	0.302	0.226	-0.737
	(54.636)	(9.322)	(0.795)	(1.252)
$hydro_{SE1}$	0.011^{**}	0.010^{*}	0.018^{***}	0.017^{*}
	(0.005)	(0.006)	(0.007)	(0.009)
$hydro_{SE2}$	-0.006	-0.007	-0.010^{**}	-0.016^{**}
	(0.004)	(0.005)	(0.004)	(0.007)
$hydro_{SE3}$	-0.018^{*}	-0.015^{*}	-0.024^{**}	-0.037^{**}
	(0.009)	(0.009)	(0.011)	(0.016)
$hydro_{SE4}$	-0.062	-0.072	-0.097	-0.202^{**}
	(0.066)	(0.063)	(0.064)	(0.092)
$nuclear_{SE3}$	-0.164^{***}	-0.158^{***}	-0.441^{***}	-0.502^{***}
	(0.051)	(0.051)	(0.075)	(0.089)
Demand				
$temperature_i$	-0.549^{***}	-0.931^{***}	-3.171^{***}	-2.712^{***}
	(0.181)	(0.241)	(0.337)	(0.414)
pvi	1.160^{***}	1.122^{***}	0.852^{**}	0.011
	(0.360)	(0.331)	(0.379)	(0.531)
$Monday$	11.186^{***}	11.221^{***}	22.011^{***}	27.625^{***}
	(1.399)	(1.430)	(1.915)	(2.324)
$Tuesday$	11.707^{***}	12.317^{***}	21.612^{***}	29.682^{***}
	(1.630)	(1.690)	(2.149)	(2.573)
$Wednesday$	12.063^{***}	12.930^{***}	23.499^{***}	30.593^{***}
	(1.563)	(1.599)	(2.389)	(2.571)
$Thursday$	12.341^{***}	12.650^{***}	22.817^{***}	29.297^{***}
	(1.573)	(1.654)	(2.290)	(2.835)
$Friday$	9.367^{***}	9.585^{***}	17.840^{***}	22.893^{***}
	(1.596)	(1.784)	(2.112)	(2.210)
$Saturday$	2.497^{***}	2.924^{***}	3.224^{**}	3.714^{**}
	(0.936)	(1.013)	(1.497)	(1.767)
$Constant$	-2.412	1.378	82.912^{*}	210.075^{***}
	(38.773)	(37.426)	(45.265)	(58.931)
Week Dummies	Yes	Yes	Yes	Yes
Observations	821	821	821	821
Adj. R2	0.773	0.775	0.771	0.684

Note: *p<0.1; **p<0.05; ***p<0.01
Heteroscedasticity- and autocorrelation-consistent (Newey-West) standard errors in parentheses.

B.2. Relative Incentives to Invest in Wind Power

Full regression results including all variables in Model 2 are displayed in Table B2.

Table B2: Regression Results - Model 2

	Dependent Variable: $UR_{wind} - UR_{electricity}$			
	SE1	SE2	SE3	SE4
	(1)	(2)	(3)	(4)
$flowbased$	-1.725	-3.886^{***}	0.655	-4.038^{***}
	(1.261)	(1.493)	(0.936)	(1.416)
$(flowbased \cdot wind_i)$	0.052	0.063^{***}	-0.012	0.151^{***}
	(0.033)	(0.019)	(0.018)	(0.049)
Supply				
$wind_{SE1}$	0.049^{**}	0.006	-0.015	-0.018
	(0.021)	(0.014)	(0.017)	(0.022)
$wind_{SE2}$	0.018^{**}	0.037^{***}	-0.001	-0.007
	(0.009)	(0.009)	(0.008)	(0.012)
$wind_{SE3}$	0.051^{**}	0.030^{**}	0.059^{***}	0.004
	(0.022)	(0.014)	(0.017)	(0.019)
$wind_{SE4}$	-0.015	-0.006	0.066^{**}	0.067^{**}
	(0.034)	(0.024)	(0.026)	(0.032)
$solar_i$	2.253	0.288	0.131	0.558^{*}
	(9.862)	(1.297)	(0.133)	(0.319)
$nuclear_{SE3}$	0.023^{*}	0.023^{**}	0.053^{***}	0.037^{**}
	(0.013)	(0.010)	(0.011)	(0.015)
Demand				
$temperature_i$	0.030	-0.031	0.060	0.131^{**}
	(0.044)	(0.042)	(0.051)	(0.058)
pvi	-0.032	-0.021	-0.044	-0.124
	(0.064)	(0.050)	(0.070)	(0.083)
$Monday$	-1.717^{***}	-1.594^{***}	-2.250^{***}	-2.828^{***}
	(0.550)	(0.356)	(0.483)	(0.611)
$Tuesday$	-1.714^{***}	-1.553^{***}	-2.751^{***}	-3.006^{***}
	(0.542)	(0.420)	(0.480)	(0.740)
$Wednesday$	-1.284^{**}	-1.241^{***}	-2.367^{***}	-2.598^{***}
	(0.534)	(0.445)	(0.472)	(0.521)
$Thursday$	-2.288^{***}	-1.667^{***}	-2.400^{***}	-2.604^{***}
	(0.559)	(0.440)	(0.554)	(0.632)
$Friday$	-1.222^{**}	-0.988^{***}	-1.408^{***}	-2.434^{***}
	(0.547)	(0.374)	(0.477)	(0.528)
$Saturday$	-0.143	-0.083	-0.422	-0.581
	(0.422)	(0.331)	(0.363)	(0.397)
$Constant$	-6.279	-8.918	-8.057	5.755
	(8.227)	(6.436)	(7.281)	(8.177)
Week Dummies	Yes	Yes	Yes	Yes
Observations	821	821	821	821
Adj. R2	0.15	0.213	0.172	0.213

Note: *p<0.1; **p<0.05; ***p<0.01

Heteroscedasticity- and autocorrelation-consistent (Newey-West) standard errors in parentheses.

B.2.1. Alternative Specification

When estimating Model 2, as specified in Equation 3 and similar to the established literature, we found a positive relationship between wind production and the relative wind unit revenue. This was surprising as it contradicts expectations of a cannibalization effect. Therefore, this required further investigation. As described in Section 7.2, we found that the timing of production seem to be a confounding factor. We accounted for this by specifying a new variable: $distribution_t^{wind}$, and extended Model 2 by including this. The updated model specification is presented in Equation 6.

$$\begin{gathered}\mathrm{UR}_t^{wind} - \mathrm{UR}_t^{electricity} = \beta_0 + \beta_1 flowbased_t + \beta_2 wind_t + \beta_3[flowbased_t \cdot wind_t] + \\ \delta' wind_{j,t} + \beta_4 solar_t + \beta_5 nuclear_t + \beta_6 distribution_t^{wind} + \beta_7 temperature_t + \beta_8 PVI_t + \eta' D_t \ + \mu_t \end{gathered} \tag{6}$$

B.3. Testing Time Series Assumptions

The Philips-Perron (PP) unit root test is used to test if a variable has a unit root, where the null hypothesis is that the variable has a unit root (i.e. is non-stationary). The PP-test rejects the null hypothesis for all variables in our main models (Model 1 and Model 2) at the 5% significance level. Based on these results, we treat the variables as stationary.

Table B3: Results from Phillips-Perron Test

Variable	Test Statistics	p-value
SE1		
UR_{wind}	-9.805	0.010
$UR_{electricity}$	-10.646	0.010
$UR_{wind} - UR_{electricity}$	-27.791	0.010
Wind	-13.873	0.010
Solar	-5.847	0.010
Hydro	-3.2074	0.087
Temperature	-4.203	0.010
PVI	-4.004	0.010
$Distribution_{wind}$	-32.7	0.010
SE2		
UR_{wind}	-10.074	0.010
$UR_{electricity}$	-10.755	0.010
$UR_{wind} - UR_{electricity}$	-25.236	0.010
Wind	-14.001	0.010
Solar	-5.999	0.010
Hydro	-3.517	0.041
Temperature	-3.925	0.013
PVI	-4.004	0.010
$Distribution^{wind}$	-31.127	0.010
SE3		
UR_{wind}	-10.555	0.010
$UR_{electricity}$	-11.088	0.010
$UR_{wind} - UR_{electricity}$	-27.866	0.010
Wind	-14.356	0.010
Solar	-4.765	0.010
Hydro	-4.8231	0.010
Temperature	-3.579	0.035
PVI	-4.004	0.010
Nuclear	-4.362	0.010
$Distribution^{wind}$	-30.293	0.010
SE4		
UR_{wind}	-12.016	0.010
$UR_{electricity}$	-11.864	0.010
$UR_{wind} - UR_{electricity}$	-24.417	0.010
Wind	-14.838	0.010
Solar	-6.982	0.010
Hydro	-3.1694	0.093
Temperature	-3.648	0.028
PVI	-4.004	0.010
$Distribution^{wind}$	-32.33	0.010

Appendix C: Generative AI Disclosure

We have used OpenAI ChatGPT-3.5 and Writefull in the writing process to improve the language, flow, and readability of the paper. After using these tools, we have reviewed and edited the content as needed. We have not used ChatGPT or any other generative AI tools as a source of information or to generate new text, but used it to assist in the preparation of the thesis. For example, to search for relevant literature and to keep up to date on news articles regarding the flow-based method. ChatGPT has also been employed to interpret errors in our program codes and to suggest possible solutions in our scripts.[24] For example, it helped to debug the R-script that tried to reorder the months in a dataset to create Figure 5. Lastly, the paper was written in LateX format, so ChatGPT has been used to improve the layout in some parts. For example, creating the title page according to a specific template. We have reviewed, edited, and revised all the content in which ChatGPT has been involved and take full responsibility for the content of the whole thesis.

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[24] All computations are done in R, version 4.2.2