Price-Spread Characteristics in the Nordic Electricity Market

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***Abstract*—In the Nordic electricity market, the inter-locational price risk is hedged by (Electricity Price Area Differential) EPAD contracts. The EPAD contracts are written based on the price spread between a specific area price and the Nordic system price (SP). By obtaining the EPAD contracts, market players seek to hedge their position against these price spreads. The EPAD market has shown a lack of liquidity in recent years [1]. We conjecture three main reasons for such illiquidity in the EPAD market. First, as theoretically demonstrated in [2], the market power in the day-ahead market can be a driver of the hedge market illiquidity. Second, the design of the EPAD contracts might not be suitable for market players. The EPAD contracts are fixed-volume contracts, and market players with varying outputs might not be willing to use them. The third reason is due to the increasing volatility of the price spreads. This paper explores the determinants of price spreads in the Nordic electricity market, challenging the hypothesis that transmission line congestion is their sole driver. We analyze the price spread determinants utilizing multivariate linear regression with augmented Generalized Least Square (GLS) for parameter estimation. Our findings indicate that while theory suggests that congestion in transmission lines is the sole causal driver of price spread variations, these factors can not explain all variations in the price spreads.**

***Index Terms*—Nordic system price, Price spread, Transmission line congestion, augmented Generalized Least Squares.**

I. Introduction

The Nordic electricity market is divided into 12 bidding areas: two areas for Denmark (DK1, DK2), one for Finland (FI), five areas in Norway (NO1, NO2, NO3, NO4, NO5), and four areas in Sweden (SE1, SE2, SE3, SE4). The day-ahead system price (SP) for the Nordic electricity market is computed as an unconstrained market-clearing reference price, assuming the transmission line capacities are infinite. The Nordic day-ahead market is coupled with the European day-ahead market through Single Day-Ahead Coupling (SDAC) model. At 10:00am CET, available capacities on interconnectors are published; market participants have until 12:00pm CET to submit their final bids to Nord Pool for the auction for delivery hours the next day. The final result of SDAC model is published and then confirmed by transmission system operators at around 1:00pm CET. The final result includes the SP for the 24 hours of the next day, area (nodal) prices for the 12 pricing areas for 24 hours of the next day, auction flows on the lines for the 24 hours of the next day, and other values like system volumes and productions.

Electricity prices exhibit complex dynamics [3], and the fact that electricity is expensive to store using current technology makes the impact of moderate shocks severe. This characteristic is also present in the price spreads, which is the difference between area prices and the SP. In addition, the deeper integration of weather-dependent energy sources such as wind and solar power into the electricity market further complicates price dynamics and hence, price forecasting [4].

Understanding the dynamics and the main drivers of the price spread are important for market participants, system operators and regulatory bodies alike. It allows (1) market participants to better optimize their risk management strategies against volatility in price spreads [5], (2) system operators to improve grid reliability during periods of high variability in price spreads, and (3) policymakers to advance the integration of renewable energy sources and ensure efficient energy use.

The importance of the topic has motivated the development of analytical price spread models, which suggest a linear relationship between price spreads and congestion factors [6]. Existing models attribute price spread to congestion on transmission lines, but fall short in explaining the dynamics of the price spread, e.g., for the purpose of forecasting. In this paper we use multivariate linear regression to analyze the main drivers of the price spread dynamics based on results for three of the twelve pricing areas in the Nordic electricity market. Our main contributions are as follows.

1) By leveraging historical data from the Nordic electricity market, we examine the theory behind price spreads in the electricity market and show that transmission line congestion is not the sole factor explaining the price spreads.
2) Using correlation and stationarity analysis, we provide a statistical characterization of the Nordic price spreads representing their fundamental properties.
3) We show that Generalized Least Square (GLS) method, when combined with ARIMA models, is effective to get efficient and consistent estimates of linear regression parameters in this context.

This paper is organized as follows: Statistical characterization of the Nordic price spreads is discussed in Section II, including analysis of the correlation structure of the price spreads and the stationarity of price spreads. Section III explores the drivers of price spreads and their relationship with transmission line congestion, including analytical and empirical analysis. Section IV provides a comprehensive analysis of the numerical results. Finally, Section V concludes the paper.

II. Statistical characterization of the Nordic price spreads

A. Data set

We use historical Nordic day ahead market data from January 1, 2015, to December 30, 2020. The period consists of 2192 days, with 12 areas and 24 hourly price data points each day. The day-ahead hourly prices for delivery of electricity at day d computed on day $d-1$ for area i are best represented as a 24-dimensional price vector $\mathbf{p}_d^i = (p_{d,1}^i, p_{d,2}^i, ..., p_{d,24}^i)^\top$. In this study we focus on the daily average prices for every area which is computed as $\overline{\mathbf{p}}_d^i = \frac{\mathbf{c}_d^i \cdot \mathbf{p}_d^i}{\mathbf{c}_d^i \cdot \mathbf{1}}$, where $\mathbf{c}_d^i = (c_{1d}^i, ..., c_{24d}^i)^\top$ is the hourly consumption (system volume) vector on day d (MWh) for area i. The resulting price $\overline{\mathbf{p}}_d^i$ is a time series with daily frequency for each area i. Correspondingly, we have the $\overline{\mathbf{p}}_d = \frac{\mathbf{c}_d \cdot \mathbf{p}_d}{\mathbf{c}_d \cdot \mathbf{1}}$ for the average SP, where $\overline{\mathbf{p}}_d$ is the SP vector for the 24 hours and $\mathbf{c}_d$ is the corresponding total consumption (system volumes). From now on, we call this $\overline{\mathbf{p}}_d$ the SP and $\overline{\mathbf{p}}_d^i$ the area price for area i and the difference, $\overline{\mathbf{p}}_d^i - \overline{\mathbf{p}}_d$, is called area price spread.

Fig. 1 shows the historical values of the price spreads ($\overline{\mathbf{p}}_d^i - \overline{\mathbf{p}}_d$) for the twelve areas. The figures shows that in certain areas, e.g., NO1, NO2, NO4 and NO5, the price spread tends to be negative (area prices are lower than the SP) while for areas like SE3 and SE4 the price spread tends to be positive (area prices are higher than the SP). Because of the significant deviations in price spreads beginning in late 2021 and continuing into 2022 and 2023, partly attributable to the geopolitical tensions, and the consequent surge in natural gas prices, we restrict our analysis to the period before the geopolitical tensions to better capture the effects of the congestion of transmission lines on price spreads. Although the Nordic region does not depend on natural gas for electricity production, its coupling with other European countries that rely on it, makes natural gas prices to have an impact on the Nordic SP [7].

B. Correlation structure

Fig. 2 shows the correlation and lag one correlation matrices between the price spreads of different areas. For the lag one correlation matrix, rows represent the current values, and the columns represent lagged (by one day) values; red corresponds to positive, and blue to negative correlation. We can observe a strong coupling between DK1 and DK2, NO1 and NO2, NO3 and NO4, SE1 and SE2, and a weak coupling between SE3 and SE4. SE1 and SE2 are also coupled with NO3 and NO4. Negative correlations between (SE1, SE2) and (DK1, DK2) show that price spreads move in opposite directions for these areas. Comparing the two correlation matrices reveals that the correlation structure between areas is similar, but the absolute values in the lag 1 correlation matrix are smaller than the corresponding values in the correlation matrix. This indicates that there is no additional information in the lagged values for the prediction of price spreads.

C. Stationarity

Theory suggests that the congestion on the transmission lines explains the area price spread [6]. If there is no congestion on transmission lines, the regional prices should equal the SP. Therefore, a significant result from the theory of electricity markets and from statistical analysis is that if the price spread for a specific area shows significant non-stationarity, it is a strong indication of a shortage of transmission capacity to or from that area. In this subsection, we analyze the stationarity of the price spreads in twelve areas. We use the Augmented Dickey-Fuller (ADF) test [8] to examine the long-run stationarity of the price spreads. The test uses the null hypothesis that a unit root is present in the times series, i.e., the time series is non-stationary. We applied the ADF test to twelve price spreads, and the test result rejected the null hypothesis of non-stationarity, suggesting that occasional congestion in transmission lines did not have a long-term effect on electricity transmission during the relevant period.

III. Drivers of Price spread

This section presents the theory behind price spreads and their relationship with congestion in transmission lines. Given the complex structure of the Nordic electricity market, including existence of non-convex constraints, accurate analytical modeling would be infeasible. Therefore, we analyze the relationship between price spread in every area and congestion in transmission lines in the Nordic region using a linear regression model.

A. Analytical Models of Price Spread

According to theory, price spreads are caused by congestion in the transmission lines. The SP is obtained by assuming that the transmission capacities are infinite, and hence there are no constraints on the flow of electricity between pricing areas. In an uncongested network, neglecting losses, optimal dispatch results in the same price over the entire network. The computed price is set to clear the market, that is, the total supply equals the total demand. The relationship between the regional prices and the SP can be formulated as [6]

$$P_i = P_s - \sum_l H_{li}\mu_l, \tag{1}$$

where P_i is the area price for area i, P_s is the SP, H_{li} are the elements of Power Transfer Distribution Factor (PTDF) matrix and μ_l is the congestion price (Lagrange multiplier of the relevant transmission-line constraint) of transmission line l. When line l is congested, the parameter μ_l will have a non-zero value and in case the line is not congested, its value will be zero. Thus, the price spread can be expressed as

$$\Delta P_i = P_i - P_s = -\sum_l H_{li}\mu_l, \tag{2}$$

which shows that in theory, the price spread ΔP_i depends on the elements of the PTDF matrix (H_{li}) and on the Lagrange multipliers of the transmission constraints (μ_l). In what follows, we will assess this analytical result empirically for the Nordic electricity market.

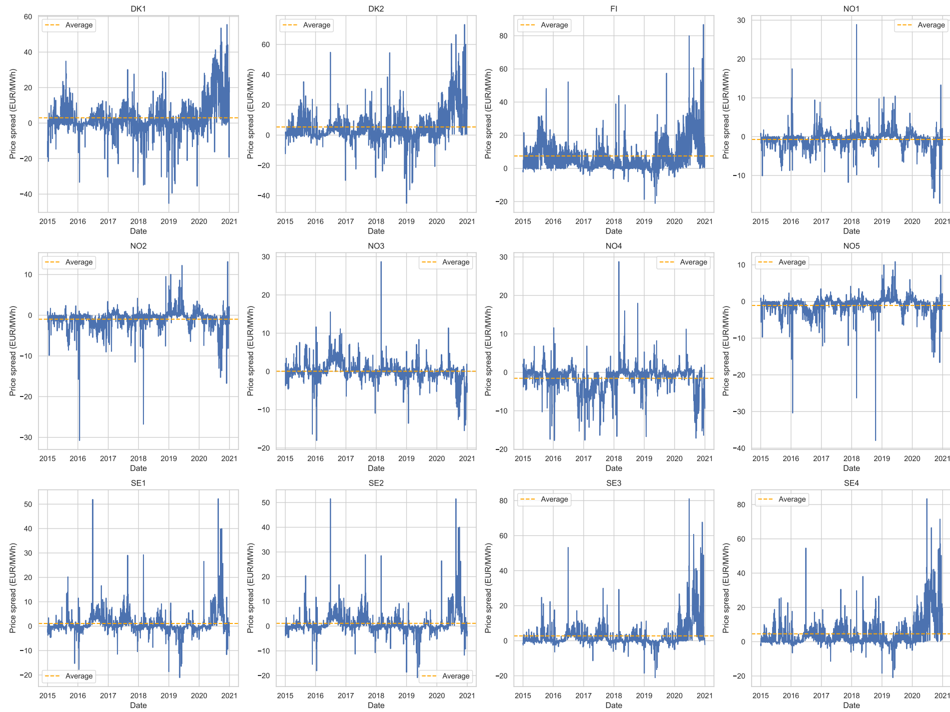
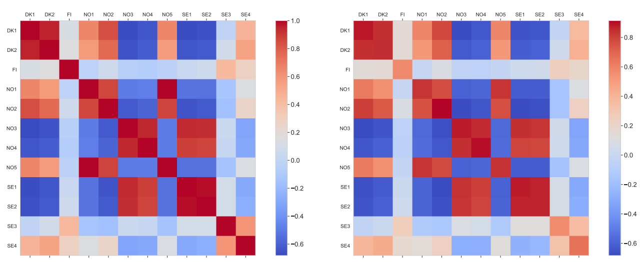


Fig. 1. Price spread in the Nordic region per pricing area, values shown are daily volume weighted averages.



(a) Correlation matrix (b) Lag 1 Correlation matrix

Fig. 2. Correlation and Lag1 correlation matrix of regional price spreads.

B. Empirical Analysis

To assess causality, we first analyze the effect of congestion on the price spread in three pricing areas. Recall that at 10:00 am CET, the available capacities are announced for all transmission lines. For each area i, we sum up the announced capacities of all lines to import to that area for 24 hours and represent it as A^i_{import}, a time series with daily frequency. Likewise, we calculate the export capacity A^i_{export}. From the SDAC calculations, we get the flows on all lines. Similarly, for each area i, we calculate the sum of the flows on all lines for 24 hours to the area i and denote it by F^i_{import}, a time series with daily frequency. Likewise, we compute the sum of the outflows F^i_{export}. To capture congestion for each area and to aid the analysis of the effect of congestion on price spreads, we define the import congestion ratio (ICR) and the export congestion ratio (ECR) as the ratio of calculated flows to announced capacities, respectively, i.e.,

$$ICR_i = \frac{F^i_{import}}{A^i_{import}}, ECR_i = \frac{F^i_{export}}{A^i_{export}}. \tag{3}$$

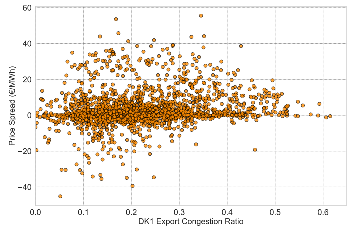
Except for some minor engineering safety-margin considerations, these two quantities are necessarily between zero and one.

Fig. 3 shows the scatter plot of price spreads for three areas, DK1, SE3, and NO4, as a function of the import and export congestion ratios. The figure shows no meaningful relationship between the export congestion ratio and the price spread for DK1. However, in the case of imports, we observe a minor positive correlation, since most of the congestion ratio is around zero and never reaches the upper limit of 1, suggesting sufficient capacity for imports. For SE3, again, the relationship between the export congestion ratio and the price spread is not clear, but there is a very clear relationship between the import congestion ratio and the price spread. For NO4, we see extreme cases of congestion both in import and export. In case of extreme export line congestion from NO4, (ECR = 1), the price spreads are negative, while during extreme import congestion (ICR = 1), the price spread is positive. Interestingly, for import or export congestion ratios close to zero, we also observe non-zero price spreads.

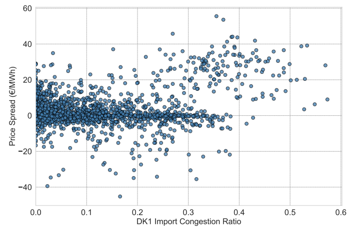
Theory suggests that the relationship between the price spreads and the congestion factors should be linear. Therefore, we use a multivariate linear regression model to find significant factors (congestion ratios) on the price spread. For each region i we use the model

$$\overline{\mathbf{p}}^i - \overline{\mathbf{p}} = \mathbf{X}\boldsymbol{\beta}^i + \epsilon^i, \tag{4}$$

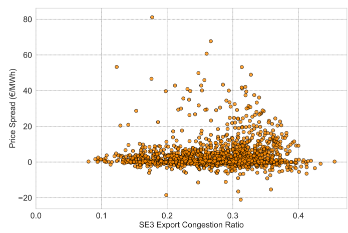
where $\mathbf{X}$ is a $d \times 25$ matrix of the form



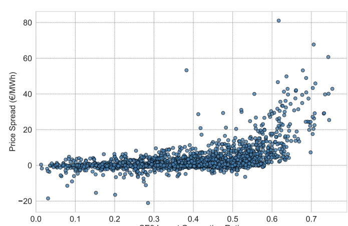
(a) DK1 - Export



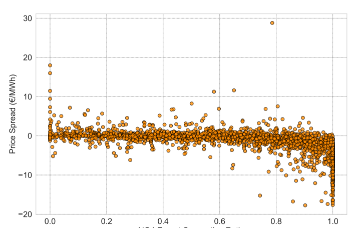
(b) DK1 - Import:



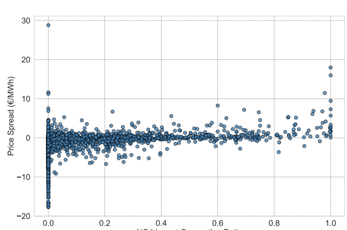
(c) SE3 - Export:



(d) SE3 - Import:



(e) NO4 - Export:



(f) NO4 - Import:

Fig. 3. Price spreads vs export and import congestion ratio for regions DK1, SE3 and NO4.

Dep. Variable:	DK1 Price Spread	**R-squared:**	0.702
Model:	GLS	**Adj. R-squared:**	0.700
Method:	Least Squares	**F-statistic:**	84.21
Date:	Sun, 09 Feb 2025	**Prob (F-statistic):**	1.35e-192
Time:	20:22:18	**Log-Likelihood:**	-6606.4
No. Observations:	2188	**AIC:**	1.324e+04
Df Residuals:	2173	**BIC:**	1.333e+04
Df Model:	14		
Covariance Type:	HC3		

	coef	std err	z	$P>\|z\|$	[0.025	0.975]
const	2.9918	0.213	14.048	0.000	2.574	3.409
ECR_DK1	-0.6795	0.187	-3.634	0.000	-1.046	-0.313
ICR_DK1	0.9709	0.210	4.624	0.000	0.559	1.382
ECR_DK2	-1.5715	0.197	-7.963	0.000	-1.958	-1.185
ICR_DK2	1.0136	0.168	6.032	0.000	0.684	1.343
ICR_FI	-1.6762	0.211	-7.936	0.000	-2.090	-1.262
ICR_NO1	-2.5228	0.354	-7.119	0.000	-3.217	-1.828
ECR_NO2	2.2326	0.404	5.527	0.000	1.441	3.024
ICR_NO3	-0.6645	0.214	-3.100	0.002	-1.085	-0.244
ECR_NO5	3.6517	0.427	8.543	0.000	2.814	4.489
ECR_SE1	1.5023	0.433	3.468	0.001	0.653	2.351
ICR_SE1	-0.5407	0.165	-3.285	0.001	-0.863	-0.218
ECR_SE2	1.9485	0.298	6.541	0.000	1.365	2.532
ICR_SE2	-0.8472	0.366	-2.318	0.020	-1.564	-0.131
ECR_SE3	1.9942	0.281	7.102	0.000	1.444	2.544

Omnibus:	288.402	**Durbin-Watson:**	2.076
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2848.049
Skew:	-0.236	**Prob(JB):**	0.00
Kurtosis:	8.569	**Cond. No.:**	5.99

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3).

Fig. 4. GLS regression results for DK1.

Dep. Variable:	SE3 Price Spread	**R-squared:**	0.634
Model:	GLS	**Adj. R-squared:**	0.631
Method:	Least Squares	**F-statistic:**	35.90
Date:	Sun, 09 Feb 2025	**Prob (F-statistic):**	6.99e-88
Time:	19:32:19	**Log-Likelihood:**	-6047.9
No. Observations:	2188	**AIC:**	1.213e+04
Df Residuals:	2173	**BIC:**	1.221e+04
Df Model:	14		
Covariance Type:	HC3		

	coef	std err	z	$P>\|z\|$	[0.025	0.975]
const	2.7639	0.172	16.091	0.000	2.427	3.101
ECR_DK1	-0.4183	0.152	-2.755	0.006	-0.716	-0.121
ICR_DK1	0.3434	0.173	1.981	0.048	0.004	0.683
ICR_DK2	0.8160	0.152	5.360	0.000	0.518	1.114
ECR_FI	-0.7737	0.154	-5.033	0.000	-1.075	-0.472
ICR_FI	-0.3433	0.124	-2.769	0.006	-0.586	-0.100
ECR_NO1	-0.5395	0.161	-3.350	0.001	-0.855	-0.224
ECR_NO2	0.9436	0.341	2.767	0.006	0.275	1.612
ECR_NO4	-0.6413	0.178	-3.608	0.000	-0.990	-0.293
ICR_NO4	-0.2692	0.115	-2.336	0.019	-0.495	-0.043
ECR_NO5	2.6223	0.404	6.492	0.000	1.831	3.414
ICR_NO5	0.4572	0.123	3.714	0.000	0.216	0.698
ECR_SE3	-1.6632	0.290	-5.727	0.000	-2.232	-1.094
ICR_SE3	4.0430	0.315	12.844	0.000	3.426	4.660
ECR_SE4	-1.2203	0.208	-5.871	0.000	-1.628	-0.813

Omnibus:	1498.269	**Durbin-Watson:**	1.980
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	79574.143
Skew:	2.602	**Prob(JB):**	0.00
Kurtosis:	32.082	**Cond. No.:**	5.53

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3).

Fig. 5. GLS regression results for SE3.

Dep. Variable:	NO4 Price Spread	**R-squared:**	0.512
Model:	GLS	**Adj. R-squared:**	0.509
Method:	Least Squares	**F-statistic:**	47.17
Date:	Sun, 09 Feb 2025	**Prob (F-statistic):**	2.16e-107
Time:	20:08:34	**Log-Likelihood:**	-4645.5
No. Observations:	2188	**AIC:**	9319.0
Df Residuals:	2174	**BIC:**	9399.0
Df Model:	13		
Covariance Type:	HC3		

	coef	**std err**	**z**	**P> $\|z\|$**	**[0.025**	**0.975]**
const	-1.5433	0.094	-16.497	0.000	-1.727	-1.360
ICR_DK2	-0.1585	0.068	-2.325	0.020	-0.292	-0.025
ECR_FI	0.5379	0.075	7.161	0.000	0.391	0.685
ICR_FI	0.2666	0.072	3.696	0.000	0.125	0.408
ECR_NO1	-0.4561	0.112	-4.073	0.000	-0.676	-0.237
ICR_NO2	0.2774	0.082	3.379	0.001	0.116	0.438
ECR_NO3	-0.1833	0.092	-1.994	0.046	-0.364	-0.003
ECR_NO4	-0.9884	0.079	-12.468	0.000	-1.144	-0.833
ICR_NO4	0.3107	0.072	4.295	0.000	0.169	0.453
ECR_NO5	-0.7286	0.142	-5.147	0.000	-1.006	-0.451
ICR_NO5	0.1639	0.070	2.342	0.019	0.027	0.301
ECR_SE2	-1.6802	0.210	-7.984	0.000	-2.093	-1.268
ICR_SE3	1.0827	0.249	4.347	0.000	0.595	1.571
ECR_SE4	0.2838	0.108	2.620	0.009	0.072	0.496

Omnibus:	903.666	**Durbin-Watson:**	1.891
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	81171.758
Skew:	1.012	**Prob(JB):**	0.00
Kurtosis:	32.770	**Cond. No.:**	10.9

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3).

Fig. 6. GLS regression results for NO4.

$$\mathbf{X} = \begin{bmatrix} 1 & (ECR\_DK_1)_1 & (ICR\_DK_1)_1 & \cdots & (ICR\_SE4)_1 \\ 1 & (ECR\_DK_1)_2 & (ICR\_DK_1)_2 & \cdots & (ICR\_SE4)_2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & (ECR\_DK_1)_d & (ICR\_DK_1)_d & \cdots & (ICR\_SE4)_d \end{bmatrix}, \tag{5}$$

and $\boldsymbol{\beta}^i = [\beta_0^i, \beta_1^i, ..., \beta_{24}^i]^\top$ is a column vector of coefficients (including the intercept).

Since price spreads have autocorrelation, the standard Ordinary Least Squares (OLS) method would produce biased standard errors, which affects hypothesis testing and confidence intervals, leading to invalid inferences. Thus, we use the Generalized Least Squares (GLS) method to estimate the coefficients $\boldsymbol{\beta}^i$. The GLS method assumes that the conditional covariance of the error term given $\mathbf{X}$ is a known non-singular covariance matrix, $\boldsymbol{\Omega}^i$, i.e.,

$$\mathrm{Cov}[\varepsilon^i \mid \mathbf{X}] = \boldsymbol{\Omega}^i. \tag{6}$$

Using GLS, the coefficients $\boldsymbol{\beta}^i$ are estimated by minimizing the squared Mahalanobis distance of the residual vector $\overline{\mathbf{p}}^i$,

$$\hat{\boldsymbol{\beta}}^i_{GLS} = \underset{\mathbf{b}}{\mathrm{argmin}}\,((\overline{\mathbf{p}}^\mathbf{i} - \overline{\mathbf{p}}) - \mathbf{X}\mathbf{b})^{\mathrm{T}} {\boldsymbol{\Omega}^i}^{-1} ((\overline{\mathbf{p}}^\mathbf{i} - \overline{\mathbf{p}}) - \mathbf{X}\mathbf{b}), \tag{7}$$

where $\mathbf{b}$ is a candidate estimate of $\boldsymbol{\beta}^i$. The solution is

$$\hat{\boldsymbol{\beta}}^i_{GLS} = \left(\mathbf{X}^T {\boldsymbol{\Omega}^i}^{-1} \mathbf{X}\right)^{-1} \mathbf{X}^T {\boldsymbol{\Omega}^i}^{-1} (\overline{\mathbf{p}}^i - \overline{\mathbf{p}}). \tag{8}$$

To estimate the matrix $\boldsymbol{\Omega}^i$, we first use OLS to estimate the residuals. We then fit an ARIMA model to the residuals of the OLS regression and then estimate the matrix $\boldsymbol{\Omega}^i$, and finally we use GLS to estimate the parameters $\hat{\boldsymbol{\beta}}^i_{GLS}$. After obtaining $\boldsymbol{\beta}^i$, we remove those variables that are not significant and then repeat the analysis with the significant factors.

IV. Numerical results

We next show regression results for three areas considered in Section **??**. Fig. 4 shows the result for area DK1, and Fig. 5 and Fig. 6 show results for areas SE3 and NO4, respectively. The results of the regression show which aggregated import and export transmission lines significantly impact the price spread variations in any area. We infer from the three regression results that every area's ICR and ECR factors significantly affect the price spread. The ECR has a negative effect on price spread for all areas, and ICR has a positive impact. These are by supply and demand rationale. In case the production of a specific area can not be exported due to export transmission line congestion, oversupply in that area reduces the price in the area, and the same is true for import. Some of the factors have interesting explanations. For example, in the case of SE3, ECR-SE4 (the ECR for SE4 region) has a negative effect on SE3 price spread. That is because area SE4 is the connection point to the countries Germany, Poland, Denmark, and Lithuania, and any congestion in exporting electricity from area SE4 to these countries decreases the price spread in SE3 since the flow is from North to South. The magnitude of each coefficient in each regression shows the relative importance of the corresponding ICR or ECR. For example, in the case of NO4, ECR-NO4 has the largest absolute value and has the strongest effect on price variations. This variable has the highest impact on reducing the difference between the NO4 price and the SP. On the other hand, ECR-FI has the highest positive impact on the NO4 price spread. The Durbin-Watson statistic shows that the problem of autocorrelation in the error terms has been solved, and the standard errors have been adjusted for this effect.

V. Conclusion

In this paper we analyzed the main drivers of area price spread in the Nordic electricity market. Our results show that existing theory does not accurately capture market operations. Even though theory suggests that price spreads have a linear relationship with congestion factors, most of the import and export lines, except for NO3, NO4, and NO5, were not congested on a daily basis. The continuous factors we defined, namely ICR and ECR, have shown to have meaningful power in explaining price spread variations, and the results show that there are other factors than congestion factors. We believe that one of the main reasons for this is nonconvex constraints included in the optimization problem solved in the Nordic day-ahead market. Our results indicate that the GLS regression could be an effective method for parameter estimation, as there is autocorrelation in the error terms. In our future work, we will further analyze the hourly data and the nonlinear relationship between price spreads and transmission line congestion, to obtain a predictive model of area price spread.

References

[1] S. kraftnät, "A review of svenska kraftnät's epad pilot 2023," 2023, available: https://www.svk.se/siteassets/english/stakeholder-portal/electricity-market/pilot-project-support/a-review-of-svenska-kraftnats-epad-pilot-2023.pdf.

[2] M. R. Hesamzadeh, D. R. Biggar, D. W. Bunn, and E. Moiseeva, "The impact of generator market power on the electricity hedge market," *Energy Economics*, vol. 86, February 2020.

[3] D. W. Bunn, *Modelling Prices in Competitive Electricity Markets*. John Wiley & Sons, April 2004.

[4] N. V. Karakatsani and D. W. Bunn, "Forecasting electricity prices: The impact of fundamentals and time-varying coefficients," *International Journal of Forecasting*, vol. 24, no. 4, pp. 635–652, 2008.

[5] Energimarknadsinspektionen, "Area price hedging and the nordic market model," 2016, accessed: 2024-10-30. [Online]. Available: https://ei.se/ei-in-english/publications/publications/reports-and-memos/2016/area-price-hedging-and-the-nordic-market-model---ei-r201611

[6] D. R. Biggar and M. R. Hesamzadeh, *The Economics of Electricity Markets*. IEEE Press, 2014.

[7] Y. A. Sadabad, M. R. Hesamzadeh, M. Bagherpour, and G. Dán, "Price dynamics of the nordic electricity market," 2025, working paper.

[8] S. E. Said and D. A. Dickey, "Testing for unit roots in autoregressive-moving average models of unknown order," *Biometrika*, vol. 71, no. 3, pp. 599–607, December 1984. [Online]. Available: https://www.jstor.org/stable/2336570