

What drives price divergence in Central and South-Eastern Europe? Evidence from flow-based market coupling

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ABSTRACT

Electricity prices in Central and South-Eastern Europe exhibited extreme divergence during the summer of 2024, followed by a period in which price differentials remained persistently higher than in Western Europe. This paper investigates the extent to which flow-based market coupling (FBMC) contributed to these outcomes by constraining cross-zonal trade. Using publicly available data, we conduct a critical network element-level empirical analysis that decomposes hourly price differences into the contributions of individual network constraints. The results show that a small number of network elements account for the majority of observed price spreads between Central and South-Eastern Europe, even after controlling for demand conditions and generation fundamentals. Regression results confirm a strong and statistically significant relationship between the available transfer capacity for commercial flow on key critical network elements (RAM scarcity) and regional price divergence. The findings point to important scope for improving FBMC implementation and underline the importance of stricter enforcement of minimum cross-zonal capacity requirements, improved transparency of capacity calculation, and stronger investment incentives for internal grid reinforcements with cross-border welfare benefits.

1. Introduction

European electricity markets are experiencing increasing structural pressures as decarbonisation, rising demand volatility and growing reliance on cross-border exchanges intensify the need for efficient use of transmission infrastructure. Despite ongoing market integration, substantial regional price differences persist across the continent, and these became particularly pronounced in Central and South-Eastern Europe during the summer of 2024. Such developments highlight the importance of understanding how congestion, system topology and capacity calculation methodologies shape the distribution of prices across bidding zones.

The EU's shift from traditional Net Transfer Capacity (NTC) allocation toward flow-based market coupling (FBMC) sought to address these challenges by embedding a physics-based representation of the grid into day-ahead market clearing. The launch of FBMC in the Core region in 2022 marked a major step in this transition, covering a large and

structurally diverse area whose internal bottlenecks and loop flows¹ play an important role in European price formation. However, the pronounced price divergence observed recently – particularly in Central and South-Eastern Europe – raises questions about whether the flow-based framework itself may contribute to limiting cross-border trade during periods of stress.

This paper examines the extent to which FBMC has influenced the emerging price patterns in Central and South-Eastern Europe. Using publicly available JAO data on critical network elements, remaining available margins (RAM), and hourly market outcomes, we identify the constraints most relevant for the High-Price Region (comprising Hungary, Romania, Serbia, Bulgaria, Greece, and Croatia) and assess their impact on day-ahead price formation.

The paper contributes to the literature by providing a detailed empirical analysis of electricity price divergence under flow-based market coupling in the Core region. The results show that a small number of critical network elements account for a large share of the

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¹ A 'loop flow' refers to a physical electricity flow arising from network physics and the meshed structure of the network, causing unscheduled electricity flows where power distributes independent of market transactions, thereby reducing available grid capacity (see Section 3.2).

observed price spreads between Central and South-Eastern Europe, even after controlling for demand conditions and generation fundamentals.

While flow-based market coupling represents a conceptual improvement over NTC-based allocation by incorporating the physical properties of the network into market clearing, the persistence of large and recurrent price divergences raises concerns about its practical implementation. Our findings suggest that these outcomes are not driven solely by exogenous supply–demand conditions, but are also closely linked to the way internal network constraints are represented within the flow-based framework. In particular, a limited number of constraints with scarce RAM can disproportionately restrict cross-zonal trade and contribute to persistent regional price divergence. The findings therefore point to important scope for improving FBMC implementation, strengthening compliance with minimum cross-zonal capacity requirements, and enhancing investment incentives for internal grid reinforcements with cross-border welfare benefits.

2. Background

In the summer of 2024, very high price spikes occurred in the early evening hours in the South-Eastern European countries. On some days these prices approached 1000 EUR/MWh, and prices in the 500–800 EUR/MWh range were common. At the same time, such high prices were not observed in Western Europe. During these same periods, prices of 100–200 EUR/MWh were typical in Germany or Austria.

Moreover, during the daytime, prices in the South-Eastern European countries were very low (sometimes close to zero) due to the high European PV production. However, as soon as PV generation dropped out of the system, high prices emerged. In the summer of 2025, we did not observe such significant price spikes in the South-Eastern European region (Fig. 1). Many studies pointed out the effect of PV cannibalization and the merit order effect on the wholesale electricity markets in Europe (Yamujala et al., 2026; Gasparella et al., 2023).

Before examining the underlying causes of the observed price divergence, it is important to establish which countries experienced high prices. To identify the relevant markets, we analysed how much the hourly prices differed from the German price during the period we examined (1 January 2024 – 31 July 2025), as Germany is one of the most important markets in Europe.² We then examined the correlation between these price differences across countries. Inspection of the empirical correlation matrix (Appendix A, Table A.1) revealed a distinct cluster of countries characterised by a dense pattern of strong pairwise co-movement. We therefore used 0.80 as a conservative threshold for identifying strong bilateral links and defined the High-Price Region as the densely interconnected group formed by these links. Based on this criterion, the High-Price Region comprises Hungary, Croatia, Serbia, Romania, Bulgaria and Greece (Fig. 2). Among these six countries, all 15 bilateral correlations are at least 0.70, and 11 are at least 0.80, confirming the strong internal coherence of the group. By contrast, Slovakia and Slovenia have only two and one, respectively, of their six bilateral correlations with the High-Price Region above 0.70, indicating more limited and peripheral co-movement. They therefore occupy an intermediate position between the High-Price Region and the Central European Region and are only weakly connected to the former.

To verify that the identified regional structure was not sensitive to the precise choice of threshold, we repeated the analysis using a lower cutoff of 0.75. Lowering the threshold further to 0.70 introduces several additional bilateral links³ but does not alter the composition of the High-Price Region. The newly added links mainly reflect weaker local or

peripheral co-movements rather than a change in the overall regional structure. These results confirm that the identification of the High-Price Region is robust to reasonable variations in the selected threshold.

3. Literature review

3.1. Potential reasons for the high prices

Several articles investigate the drivers behind the high electricity prices in South-Eastern Europe in summer 2024. The two most important factors identified are demand-side conditions and the operation of flow-based market coupling. Blecich et al. (2025) show that Croatian electricity consumption was extremely high during the summer of 2024, particularly in July. Peak load exceeded the previous year's level by more than 5%. This was primarily due to a heatwave and the widespread use of air conditioning.

ICIS (2024) summarises the key factors influencing high electricity prices in South-Eastern Europe. According to the analysis, the most significant factor was increased demand. Due to exceptionally high temperatures in July 2024, electricity consumption was more than 7% higher than in the previous year. Additionally, dry conditions reduced hydro generation and affected nuclear production (for example, the Paks nuclear power plant had to reduce its output).

The ACER (2025a) report highlights two notable phenomena. First, summer electricity demand in South-Eastern Europe is highly sensitive to rising temperatures. The analysis found that a 1°C increase in temperature leads to an average rise of around 100 MW in electricity consumption per country across Europe. In Greece, however, this figure is nearly 400 MW. Second, when the market becomes tight, supply-side bidding behaviour changes. This results in higher prices and creates conditions in which exercising market power becomes more profitable. However, tight market conditions are highly unpredictable over time, which reduces the incentives and opportunities to exercise market power. For example, while the major high-price episodes occurred during the summer of 2024, similar periods emerged in winter 2025, illustrating the temporal variability of market stress situations. In addition, when market splitting occurs, it typically affects multiple countries simultaneously within the higher-price SEE region, further limiting the scope for exercising market power.

Balkan Energy (2024) finds that the most important factor behind high prices in South-Eastern European countries was flow-based market coupling, which constrained import possibilities from Western Europe. Other transmission-related issues included maintenance on the RO–BG and HU–RO interconnectors. There were also outages affecting baseload generation, such as maintenance at the Kozloduy nuclear power plant. Finally, another reason for the high prices was the increase in selling offer prices across all markets, particularly in the Greek market.

However, it should be emphasized that most of the literature finds that FBMC improves price convergence. The remaining obstacles are generally not attributed to the introduction of FBMC itself, but rather to underlying physical network bottlenecks. One important advantage of FBMC is that it reveals these physical constraints more transparently than the previous NTC-based mechanism. In addition, the flow-based framework also makes bottlenecks within domestic transmission grids more visible, thereby providing clearer signals regarding the location and nature of structural network limitations.

3.2. Flow-based methodology, key concepts and price formation

European electricity markets increasingly rely on flow-based market coupling (FBMC) to allocate cross-zonal transmission capacity in a manner that reflects the physical behaviour of a meshed transmission network. The methodological rationale for FBMC arises from a fundamental observation: power does not flow along contractual paths but follows Kirchhoff's laws, distributing across all parallel lines in proportion to their impedances (a cause of loop-flows in a meshed electricity

² Germany accounts for nearly 20% of EU27 electricity consumption in 2025, according to the EMBER Energy database, and—being centrally located in Europe with strong interconnections to neighbouring countries—plays a key role in regional power market dynamics.

³ GR–HR, EE–FI, GR–HU, AT–CH, FI–SE, SI–SK.

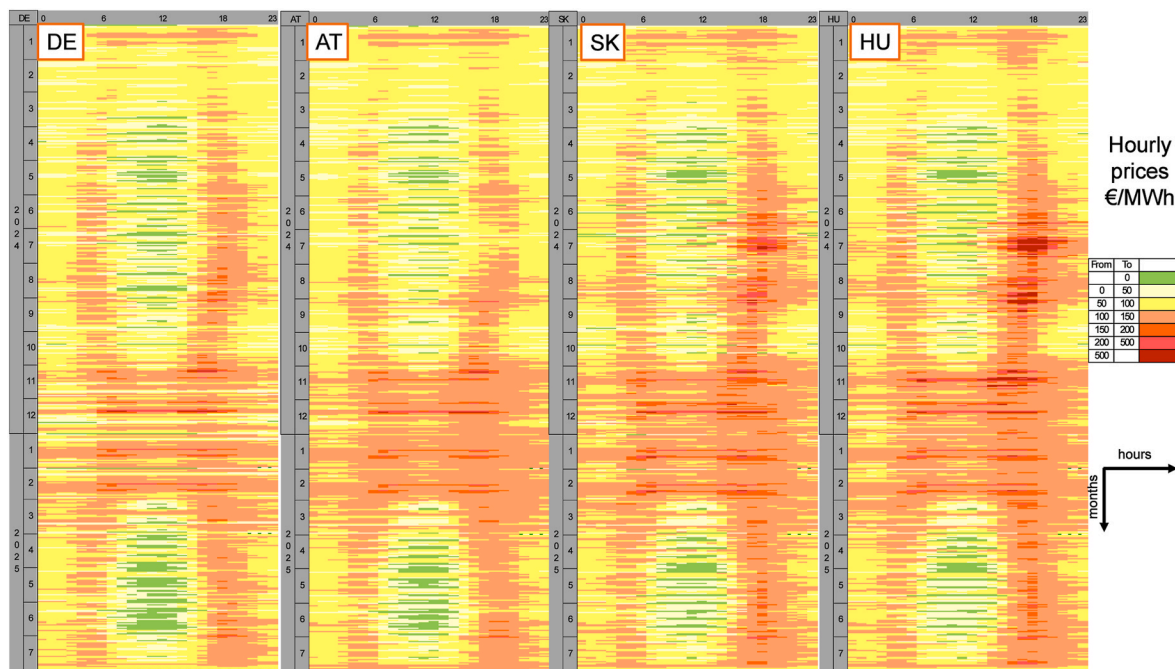


Fig. 1. Day-ahead hourly market price in some European countries, 1 January - 31 July 2025
Source: Own figure based on [EMBER \(2025\)](#) database

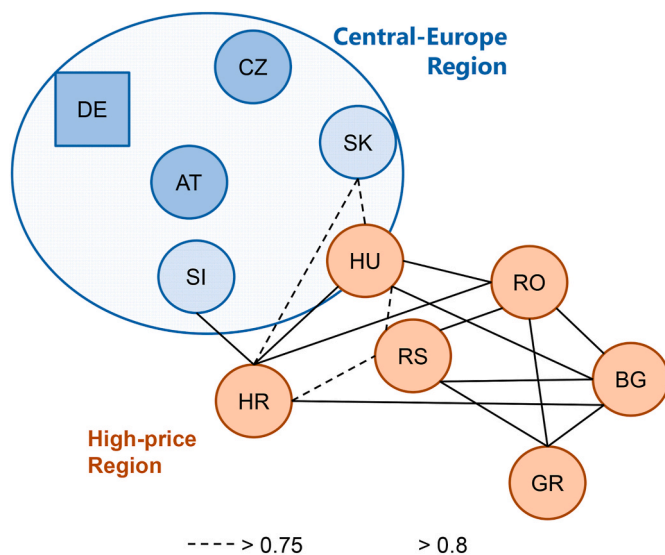


Fig. 2. Correlation of price differences compared to German day-ahead market prices
Source: Own calculations based on hourly day-ahead market prices

network). As [Schönheit et al. \(2021\)](#) emphasize, any market design that ignores this physical interdependence – such as bilateral Net Transfer Capacity (NTC) allocation – leads to suboptimal use of the grid and induces inefficient dispatch. Earlier conceptual work by [Van den Bergh et al. \(2016\)](#) similarly demonstrates that bilateral capacity limits fail to account for loop flows, parallel path interactions, and the system-wide implications of commercial exchanges. These analytical insights motivated the shift to a flow-based framework that embeds a simplified network model directly into the market-clearing mechanism. However, [Felten et al. \(2021\)](#) emphasize that although the flow-based method is more efficient than the previous NTC-based method, it can never be perfect because the inherent simplifications of the zonal system inevitably distort physical reality, resulting in welfare losses compared

to nodal pricing.

The foundational conceptual framework and methodology of CWE (Central Western Europe) flow-based market coupling are well documented in the academic literature (see, for example, [Van den Bergh and Delarue, 2016](#); [Schönheit et al., 2021](#); [Felling, 2023](#)). Academic literature on the Core region remains relatively limited, but the flow-based methodology and the construction of the feasible trading domain are discussed in detail by [Nagy et al. \(2025\)](#). A comprehensive presentation of the mathematical and geometric properties of the flow-based domain would go beyond the scope of the present paper. More detailed explanations of the FBMC methodology can be found in the Core Day-Ahead Capacity Calculation Methodology published by ENTSO-E, as well as in [Nagy et al. \(2025\)](#). The following section therefore focuses only on the main steps of the process and the concepts necessary for understanding the subsequent empirical analysis.

In operational terms, flow-based capacity calculation begins with the construction of a D-2/D-1 base-case grid model. Transmission system operators jointly forecast load, generation – including intermittent renewables – and network topology, producing a set of reference flows on each transmission element. This reference state serves as the benchmark against which all market-induced deviations are evaluated. [ENTSO-E \(2019\)](#) details this process and highlights its importance for ensuring a consistent starting point across transmission system operators (TSOs) before market coupling occurs.

A central analytical tool within this framework is the Power Transfer Distribution Factor (PTDF). PTDFs measure the sensitivity of line flows to changes in net commercial positions. They are initially computed at the nodal level, indicating how a 1 MW injection at a node distributes across all monitored lines. Since European electricity markets operate on a zonal basis, these nodal sensitivities must be aggregated into zonal PTDFs. This transformation requires Generation Shift Keys (GSKs) and Load Shift Keys (LSKs), which determine how incremental changes in a zone's net position are distributed across internal generation and load within the bidding zone. As [Schönheit et al. \(2021\)](#) show, different assumptions regarding these allocation keys can lead to different zonal PTDF matrices and therefore different feasible trading domains. Not all network elements can be included in the flow-based domain, as doing so would be both computationally infeasible and unnecessary. Therefore,

TSOs identify a subset of lines termed Critical Network Elements (CNEs). A line becomes a CNE if its loading is sufficiently sensitive to changes in zonal net positions, with sensitivity measured directly through PTDF magnitudes. In the Core flow-based methodology, a transmission line is included as a CNE if its loading is sufficiently sensitive to cross-zonal exchanges. More precisely, a line is selected if the absolute value of at least one zone-to-zone PTDF exceeds the 5% threshold as defined in the Core Day-Ahead Flow-Based Capacity Calculation Methodology (ENTSO-E, 2019). In addition to N-0 conditions, the N-1 security criterion requires TSOs to assess how each candidate line would behave under the outage of another element; lines that would risk overload under such contingencies are included as CNECs (CNE with Contingency). Historical congestion patterns, structural bottlenecks, and operational experience also influence the final selection. This curated CNEC set balances completeness with computational tractability and ensures that only network elements relevant to cross-border exchanges constrain the market.

Once CNECs are identified, TSOs determine the Remaining Available Margin (RAM) for each monitored element. The RAM represents the capacity available for additional commercial flows beyond the base case and is computed by subtracting forecasted flows (the flows without any commercial exchange ($F_{0,all}$), the flows from assumed commercial exchanges outside the Core region (F_{UAF})) and a Flow Reliability Margin (FRM) from the element's maximum admissible flow (F_{max}). The FRM accounts for model uncertainty, forecast error, and the inherent limitations of zonal representation. In certain cases, expected remedial actions – such as redispatch or phase-shifting transformer adjustments – may increase the RAM, provided these actions are reliable and coordinated. Van den Bergh and Delarue (2016) demonstrate that RAMs play a decisive role in determining the size and shape of the flow-based domain, and thus the extent to which the network can support cross-zonal trade.

Due to its importance, a 70% minimum RAM rule was introduced by EU regulation 2019/943 to ensure that TSOs make at least 70% of each critical network element's physical capacity available for cross-zonal electricity trade. Although the 70% minimum RAM rule is often associated with cross-border transmission capacity, it also applies to internal CNECs whenever these elements constrain cross-zonal exchanges within the flow-based domain. The minimum 70% rule is also denoted as the required allocated capacity (MinRAM factor) in the FB calculations. This requirement became fully binding from January 2026, although temporary derogations and national action plans may apply in cases where full compliance is not yet feasible.

The flow-based domain emerges from the combination of zonal PTDFs and RAM values. This domain is a convex polyhedron representing all feasible combinations of zonal net positions that satisfy the set of linear network constraints. The day-ahead market coupling algorithm⁴ then solves a welfare-maximising optimisation problem over this domain.

Price formation within FBMC follows directly from the binding constraints of this optimisation problem. Zonal price divergence arises precisely when one or more CNECs bind at the optimum. Each binding constraint is associated with a shadow price, representing the marginal welfare gain from relaxing that constraint by 1 MW. The contribution of a binding CNEC to the price of a zone equals the shadow price multiplied by the zone's PTDF on that CNEC. Hence, the price difference between two zones equals the sum, over all binding constraints, of the shadow price times the difference in their PTDFs. In the Core region, this mechanism is further shaped by the Long-Term Allocation (LTA) domain inclusion, which ensures that the day-ahead flow-based domain is at least as permissive as the long-term allocated capacities. LTA inclusion effectively adds additional constraints – or relaxations of constraints –

into the feasible domain to guarantee that all long-term rights remain simultaneously feasible in the day-ahead market. When these LTA-driven adjustments become binding, they can modify which constraints influence price formation or alter the effective RAM available on certain CNECs.

The Core region, which became fully operational under flow-based market coupling in 2022, exemplifies these dynamics. As ENTSO-E (2022) and ACER reports document, this region features an exceptionally large and structurally diverse grid with pronounced internal bottlenecks, strong loop flows, and significant north-south and east-west transit flows. These characteristics lead to a larger and more heterogeneous CNEC set than in earlier flow-based regions such as Central Western Europe. The complexity of the Core network implies that constraints are more likely to bind and that the resulting price patterns may be more dispersed. The academic literature, including Schönheit et al. (2021) and Finck (2021), emphasises that such complexity magnifies the influence of modelling choices – particularly GSK selection and PTDF aggregation – on market outcomes. Consequently, FBMC in Core region simultaneously enhances the physical realism of capacity allocation and introduces additional challenges in transparency, predictability, and stakeholder interpretation.

3.3. Empirical analysis and forward-looking modelling literature on FBMC

The expansion of FBMC to Eastern European countries was expected to further reduce price spreads within the Core region, and several assessments have quantified this impact. In the following, we examine studies that have carried out empirical analysis of the impacts of introducing the FBMC methodology, focusing on the various drivers of the price convergence and the resulting welfare gains, as well as studies based on scenario modelling, that quantify the possible outcomes of various policy improvements in the methodology.

Although focusing on the introduction of FBMC in 2015 in the CWE region, the aim of the analysis of Ovaere et al. (2023) was similar to this study. Using hourly data from 2013 to 2017, they examined the impact of the new methodology on cross-border trading and price convergence. They found that the initial benefits were approximately 30% greater in the short term than in the long term: the average RAM value of critical transmission lines in the region decreased by 300 MW during the five months after the introduction of FBMC. After controlling for variables describing market conditions, they found a positive correlation between RAM values and price differences between countries. The authors argue that TSOs face a trade-off between technical system reliability and market efficiency, which they may have adjusted in the months following the introduction of FBMC. The authors recommend regulatory measures related to MinRAM criteria, or the provision of other incentives for TSOs, to help unlock the full potential of cross-border trade.

Nagy et al. (2025) focused specifically on extending the FBMC to CEE (Central Eastern European) countries. They highlighted the positive outcomes of price spread convergence, which resulted in significant welfare gain. However, this development occurred alongside high price volatility. They compared the key outcomes of the Net Transfer Capacity and Flow-Based Coordinated Capacity Calculation methodologies, drawing on data from the period of their parallel application during the demonstration and test phase of the FBMC between October 2021 and April 2022. The study found that the FBMC resulted in higher producer and consumer surplus, increasing social welfare by 0.92% (~ EUR 3.37 billion). However, high price spreads (above 200 EUR/MWh) became more frequent, which could be statistically linked to TSOs' intensive use of initial validity adjustments (IVA) that reduce the RAM of CNECs to avoid operational security risks. Following the go-live of the FBMC, they observed a positive contribution to price convergence and an increase in the number of low-spread hours, however the volatility in prices remained high. The authors conclude that a single active constraint can drive price spreads across multiple bidding zone borders and cause

⁴ In the Core Region, the market clearing process relies on EUPHEMIA (Pan-European Hybrid Electricity Market Integration Algorithm).

bidding zones, especially those with external borders to the Core Capacity Calculation Region, such as Slovakia, Hungary, and Romania, decoupling from Core region prices.

Léchenet (2025) also conducted an empirical investigation into the long-term convergence of electricity prices within the Core Region, differentiating between markets that adopted FBMC in 2015 and those joining in June 2022. The study employed a price dispersion indicator, constructed to capture the magnitude of price differentials between country pairs, with a theoretical value of zero under complete price convergence. Using this indicator as the dependent variable, separate OLS regression models were estimated for each subset of countries, with explanatory variables including a post-FBMC extension dummy variable, fuel and CO₂ prices, electricity generation by various technologies, and load levels. The results showed a permanent and significant decrease in price differentials for the countries joining in 2022. However, the estimations did not consider within day price variations or how the effects might differ among individual countries.

Beyond network constraints, other fundamental factors are driving price differentials. ACER (2025b) analysed the price differential in the summer of 2024 between the central core countries and the eastern-southern border countries (e.g. Hungary, Romania and Bulgaria), which exceeded 1000 EUR/MWh in many hours. This extreme price spread was caused by a combination of network constraints and supply and demand factors, such as a sharp reduction in PV production in the late afternoon and early evening, increased consumption due to high temperatures, and maintenance work on some key transmission elements in Austria and Hungary.

Several studies offered ideas for enhancing the FBMC methodology by recommending improvements and testing them via modelling various scenarios, comparing them to actual market results.

Marjanovic et al. (2018) investigated two scenarios for 2020, one including Western European countries (Germany, the Netherlands, France, Belgium and Austria) and another including future members from the CEE region. They showed a potential 150 million EUR welfare gain with the increasing regional coverage of the Core FB and reducing the need for redispatch for the newcomer countries. Their modelling also indicated that the wider regional coverage more than doubles the number of the restricting network elements. Finck (2021) provides a detailed review of articles on FBMC published before 2021. The review focused on both the theoretical foundations of FBMC and the potential impacts of the planned expansion of the FB region. He also carried out a model-based assessment for the year 2025. He projected that the reduction in price spreads is mainly due to the higher availability and utilisation of baseload capacities (nuclear power plants and, to a lesser extent, lignite power stations).

Bucksteeg et al. (2024) estimated the overall welfare gain potential of the Core region to be 215 million EUR due to the FBMC in 2022, but with the condition of integrating redispatch potential in the market clearing stage. Several other authors modelled the possible improvements in FBMC through better optimising redispatch, including Lang et al. (2020), Thomassen et al. (2024) and Henneaux (2021). ACER (2025b) estimated that meeting the 70% rule in the Core region would increase consumer welfare to EUR 580 million per year, up from the current level of EUR 240 million in 2024. However, they also highlight the challenges in achieving the 70% target. In 2024, the region's average was 54%, with only Czechia and Slovenia reaching the target. High remedial costs across EU Member States are also highlighted: 60 TWh of redispatching in 2024 cost a total of EUR 4.3 billion.

While the existing literature provides substantial evidence on the welfare gains and price convergence effects of FBMC, it typically relies on aggregate indicators, model-based simulations, or reduced-form empirical approaches. However, much less attention has been paid to the micro-level mechanisms through which individual network constraints shape price formation in practice. In particular, there is limited empirical evidence linking specific critical network elements (CNECs), their RAM values, and hourly price divergence outcomes using publicly

available data.

To address this gap, this paper develops a critical network element-level empirical framework that decomposes price differences into the contributions of individual constraints, and empirically links RAM scarcity to hourly price divergence using publicly available data.

4. Analysis of the most important critical network elements

To examine how FBMC influences regional price formation, we assessed the impact of critical network elements on price differences within a two-stage analytical framework. In the first step, we identified which network elements are most critical from the perspective of the High-Price Region. The methodology used for this identification, along with the required data inputs, is presented in the following subsection. After determining which CNECs are most relevant for the price formation in the region, we examined their impact through the evolution of their remaining available margin (RAM). This was carried out in a second step within a regression framework that jointly considers supply- and demand-side factors. The detailed methodology and the results of this second step are presented after the CNEC analysis.

4.1. Methodology for CNEC impact analysis

In the flow-based domain framework, the bilateral price difference arising along a given CNEC between two bidding zones in a specific hour can be calculated exactly using publicly available data from the JAO database. The price difference between zones A and B in hour j, attributable to the capacity limitation imposed by the flow-based domain, can be determined using the following formula:

$$PS_{A-B,j} = \sum_{i=1}^n (PTDF_{A,i} - PTDF_{B,i}) \cdot SP_{j,i}$$

where:

- PS_{A-B} : Price difference between price zone A and B in hour j
- $PTDF_{A,i}$: shows how a change in the net position of country A by 1 MW affects the flow on the i-th CNEC
- $PTDF_{B,i}$: shows how a change in the net position of country B by 1 MW affects the flow on the i-th CNEC
- $SP_{j,i}$: The shadow price of the i-th CNEC in hour j (representing the increase in total welfare associated with a 1 MW increase in the capacity of the CNEC)

If the LTA domain is not active, the resulting value is identical to the total price difference between the two bidding zones. If the LTA domain is active, the calculation is similar, but its price effect must also be added. In this case, the most practical approach to determine the full price difference is to rely on the alpha factor. From the perspective of price differences, the alpha factor indicates which domain imposes the binding constraint and in what proportion. In other words, it shows what share of the resulting price difference is attributable to the FB domain, and consequently, what share (1- alpha factor) is linked to the LTA domain. Accordingly, once the price difference associated with the FB domain has been determined, dividing it by the alpha factor yields the full price difference between the two bidding zones. An exceptional case arises when the alpha factor equals zero. In this situation, any price difference between the two zones must originate exclusively from the constraints of the LTA domain, and the bilateral price spread must therefore be taken directly from the "Price Spread" table in the JAO Publication Tool (JAO, 2023).

For the purposes of our analysis, it is particularly important that the calculation logic described above allows not only the determination of the price difference between two bidding zones caused by the FB domain, but also the identification of the contribution of each individual CNEC to this price difference. The numerical example in Fig. 3 illustrates

	[1]	[2]	[3] = [1] - [2]	[4]	[5] = [3] * [4]
Cnec Name	PTDF: DE	PTDF: HU	DE-HU	ShadowPrice	Price difference
Obersielach- Podlog 247	0.00428	-0.01619	0.0205	405.31	8.30
Peinting- St. Peter 258	0.00318	-0.08184	0.0850	105.65	8.98
Levice- God	0.00708	-0.18667	0.1938	138.45	26.82
TRRbsiori 400/220 1	0.00119	0.00239	-0.0012	341.46	-0.41
V.Dur- Levice 1	0.00114	-0.12486	0.1260	960.27	120.99
Price difference by FBdomain (EUR/MWh):					164.7
Alpha factor:					1
Total pricespread DE-HU (EUR/MWh):					164.7

SUM[5]

[6]

[5] / [6]

Fig. 3. Calculation example of price differences using JAO database (15:00 UTC on 2024-07-17)
Source: REKK calculation based on JAO database.

this calculation.

The list of critical network elements for a given hour, along with their key parameters, is provided in the “Active FB constraints” table of the JAO Publication Tool.⁵ The database contains the PTDF matrix values and the shadow prices for each active FB constraint - i.e., the specific physical grid limits that actually restrict the flow of electricity during the market clearing process. In our example, we determine the price difference between Germany and Hungary for hour 15:00 UTC on 2024-07-17.

As shown in the example, a total of 5 network elements constituted active constraints in the examined hour. In terms of the Germany–Hungary price difference, the largest impact [5] arises along the constraint of the V. Ďur–Levice 1 line (121 EUR/MWh), while the second-largest impact is associated with the Levice–Göd network element (26.8 EUR/MWh). The price difference induced by the FB domain amounts to 164.7 EUR/MWh in total, and since the LTA domain was not active in the hour under consideration (alpha factor = 1), the full price difference also equals 164.7 EUR/MWh.

After identifying the network elements that are critical from a price-impact perspective, we examined how their remaining available margin (RAM) evolves and how this evolution is related to emerging contingencies and, consequently, to price formation. When a network element represents an active constraint, its RAM value for the relevant hour appears in the previously discussed *Active Constraints* table.

For the analysis, and for the subsequent regression framework, it was necessary to supplement these data with RAM values for those hours in which the network element was not an active constraint but was still included in the flow-based domain computational framework. We obtained these additional values from the *Final Computation* table⁶ of the JAO Publication Tool using the following procedure.

In the *Final Computation* table, multiple RAM values may be associated with a given network element in the same hour, reflecting different CNEC configurations. For hours in which the network element was not an active constraint, we selected the smallest RAM value corresponding to the flow direction that typically constitutes the limiting direction for that element. In other words, we retained the most restrictive RAM value reported for the branch within the relevant flow direction.

This approach is intended to identify the most restrictive non-binding representation of the branch in each hour. Higher RAM values within the same limiting direction may correspond to less restrictive contingencies and are therefore less informative for assessing how close the branch is to becoming binding. Using the lowest RAM value within the relevant direction thus provides a conservative benchmark for comparison with binding hours, as it reduces rather than amplifies the observed difference between RAM values in binding and non-binding situations. Empirically, the selected lowest-RAM configuration often corresponds closely to the contingency under which the branch later becomes an active constraint.

The analysed period covers data from 1 January 2024 to 31 July 2025.

4.2. Results of the CNEC identification and their impacts

An analysis of Core region market data reveals that a small number of CNECs cause regional price peaks. Along the borders separating the High-Price and Central-European Regions (AT–HU, SK–HU, SI–HU, and SI–HR), the five most influential CNECs account for approximately 84% of the observed price differences (Fig. 4). Among these, two internal network elements – the V. Ďur–Levice line in Slovakia and the Neusiedl–Wien line in Austria – together explain nearly 60% of all congestion-related effects. The remaining three critical elements are cross-border lines located on the Czech–Slovak, Slovak–Hungarian, and Slovak–Ukrainian borders. As the FBMC methodology relies on the actual physical interconnectedness of the grid, it also considers internal network elements within bidding zones, which can become binding and thus restrict cross-zonal exchanges. Furthermore, in highly meshed grids, loop flows can create physical bottlenecks that influence prices even in non-neighbouring zones. This explains why congestion is, for the most part, not caused by interconnectors at the borders of the high-price region.

The detailed examination of border-level price spreads also shows that congestion does not always increase price divergence directly. In some cases, certain constraints may even reduce the price difference between two neighbouring markets. For example, congestion on the Czech–Slovak interconnector tends to narrow the Slovak–Hungarian price gap, since it prevents Slovak prices from falling to the lower levels observed in Western Europe. However, it simultaneously

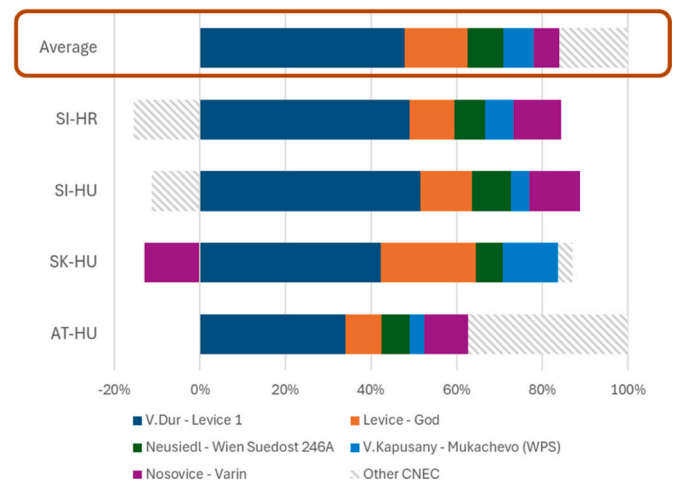


Fig. 4. Impact of critical network elements on price spreads across the borders between the analysed regions
Source: REKK calculation based on JAO database.

⁵ Available at: <https://publicationtool.jao.eu/core/shadowPrices>.

⁶ Available at: <https://publicationtool.jao.eu/core/finalComputation>.

amplifies the overall price difference between Central and South-Eastern Europe, as it limits the inflow of cheaper electricity from the West into the region.

The main characteristics of the five CNECs most relevant to our analysis are summarised in Table 1, including their description, maximum admissible power flow, nominal voltage level, associated contingency (N-1), and constrained flow direction. It should be noted that the reported contingencies and constrained directions represent the most frequently observed configurations in the sample and do not necessarily apply to every binding hour.

The five most influential CNECs differ greatly in both their frequency and their impact on price formation. The V. Ďur-Levice (SK) line proved to be the most influential overall, constraining trade for more than 1400 h during the analysed period and associated with an average DE–HU price spread of 48 EUR/MWh. In contrast, Neusiedl–Wien (AT) was binding in fewer than 100 h, yet its impact was extremely high (average spreads exceeded 110 EUR/MWh) whenever it became critical. The Nosovice–Varín (CZ–SK) element displayed the opposite pattern: it was binding relatively often (around 13% of hours) but generated a more moderate spread of about 18 EUR/MWh on average (Fig. 5).

Beyond the differences observed in the number of binding hours and the average price spreads associated with each CNEC, the analysed network elements also differ substantially in terms of their maximum zone-to-zone PTDF values. According to the Core methodology, a network element becomes part of the active flow-based domain when at least one zone-to-zone PTDF exceeds 0.05. Among the CNECs analysed, this threshold is particularly relevant in the case of Neusiedl–Wien Suedost 246A. During the hours in which this network element was active, its maximum zone-to-zone PTDF exceeded 0.06 in only 40% of the cases, while the highest observed value over the full sample period was 0.08. By contrast, for the other four CNECs, the corresponding PTDF values exceeded 0.1 in every active hour.

The set of critical transmission lines driving price formation in the region has changed considerably over time. The V. Ďur-Levice line in Slovakia was highly influential, particularly during summer 2024 and again around year-end 2024, when it frequently constrained cross-border flows and contributed to sustained price differentials. The Neusiedl–Wien connection in Austria had a rare but severe impact, most notably in late June and July 2024, when it coincided with exceptionally high price spreads. The Levice–Göd (SK–HU) line emerged as another key element, exerting recurrent and substantial effects across multiple periods, especially in summer 2024 and spring-summer 2025. In contrast, the Nosovice–Varín (CZ–SK) line appeared frequently but generated only modest price impacts, reflecting its relatively limited influence on overall congestion patterns. Finally, the V. Kapušany–Mukachevo (SK–UA) interconnector exhibited sporadic but pronounced constraints, particularly during winter 2024/25 and mid-2025 (Fig. 6).

In the flow-based market coupling framework, Remaining Available Margin (RAM) is the portion of a transmission line's capacity that remains available for commercial exchanges after accounting for base flows, reliability margins, and long-term commitments. A reduction in RAM consistently leads to larger price spreads between bidding zones.

Our empirical analysis confirms this strong correlation between RAM and price differences on the key CNECs. In July 2024, capacity scarcity was most apparent in the afternoon across almost all critical elements – except Levice–Göd – coinciding with episodes of extreme price spreads. In September 2024, RAM scarcity was particularly pronounced on the Nosovice–Varín and V. Ďur-Levice lines, primarily during afternoon hours. During January–February 2025, the Levice–Göd line showed the

lowest RAM values, aligning with the largest price differentials of the period. By summer 2025, afternoon price peaks re-emerged, albeit less extreme than in 2024, once again driven by recurring RAM scarcity on the same network elements (Fig. 7).

Another important dimension is RAM volatility. Intra-day fluctuations of 20–25% are common, and even consecutive days at the same hour can exhibit twofold differences in available capacity. Such instability increases uncertainty for traders, system operators, and regulators, underscoring the need for more predictable and transparent capacity allocation within the FBMC framework. RAM values are only announced a few hours before day-ahead market closure, further increasing trade uncertainties.

A closer quantitative look at July 2024 provides clear empirical evidence of the strong relationship between RAM scarcity and price divergence.

For both elements, the contrast between binding and non-binding hours is striking. During periods when these CNECs are not active constraints, average RAM levels are substantially higher, and DE–HU price spreads remain moderate. In contrast, when the V. Ďur-Levice line becomes binding, average RAM falls by more than 20%, while the corresponding price spread rises by roughly 170%. Similarly, during hours when the Neusiedl–Wien line is active, available capacity is around 25% lower, and the associated DE–HU price difference increases sixfold compared to unconstrained hours (Table 2).

As Table 3 demonstrates, compliance with the 70% rule remains uneven, particularly on high-impact internal network elements. The minimum required allocated capacity (MinRAM factor) on the two most influential internal lines (V. Ďur-Levice 1 in Slovakia and Neusiedl–Wien in Austria) is currently well below the 70% threshold. Moreover, when the V. Ďur-Levice 1 element acts as an active constraint, the ex-post calculated RAM factor frequently falls short even of this lower interim level.

Given that these lines significantly influence price differentials between the High-Price Region and Central Europe, ensuring compliance with the minimum RAM requirement is essential to enhance price convergence, improve market efficiency, and maximise social welfare.

5. Regression analysis of day-ahead market price differentials

5.1. Methodology and data

We conducted a regression analysis to examine the impact of the RAM values of the most relevant network elements, together with other explanatory factors, on price differences between Germany and the High-Price Region, as well as between Germany and Hungary. To ensure valid statistical inference, the regressions were estimated using Newey–West (1987) heteroskedasticity- and autocorrelation-consistent standard errors with a maximum lag length of 24 (corresponding to 24 h). This approach is particularly appropriate for hourly electricity market data, where both price spreads and grid capacity constraints may persist across adjacent hours, potentially leading to serial correlation in the error terms.

The dataset combines hourly load, generation, and day-ahead price data from the ENTSO-E Transparency Platform with hourly RAM values of the relevant critical network elements published by JAO. The sample covers the period from 1 January 2024 to 31 July 2025.

We estimate six regression specifications based on two alternative dependent variables: (1) the spread between the German day-ahead market (DAM) price and the weighted regional average price of the

Table 1
Main characteristics of the selected CNECs.

CNEC Name	Description	Maximum admissible power flow (MW)	Nominal voltage level (kV)	Typical Associated Contingency (N-1)	Typical Constrained Direction
V.Dur - Levice 1	Internal line within Slovakia	1455-1839	400	V.Dur - Levice 2	DIRECT
Levice - God	Cross-border line between Slovakia and Hungary	1386	400	R.Sobota – Sajoivanka	DIRECT
Neusiedl - Wien Suedost 246A	Internal line within Austria	312	220	Gyor – Wien	OPPOSITE
V.Kapusany - Mukachevo (WPS)	Cross-border line between Slovakia and Ukraine	1088-1372	400	R.Sobota – Sajoivanka	DIRECT
Nosovice - Varin	Cross-border line between Slovakia and Czechia	1550	400	Krizovany – Sokolnice	DIRECT

Source: REKK calculation based on JAO database

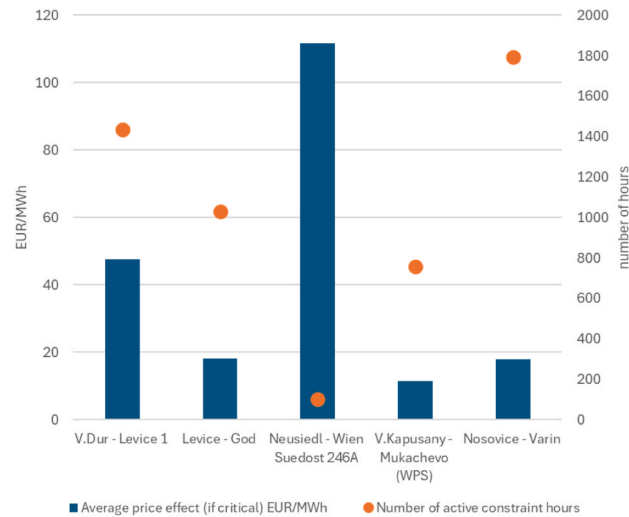


Fig. 5. The impact of the CNECs on the DE-HU price difference

Source: REKK calculation based on JAO database.

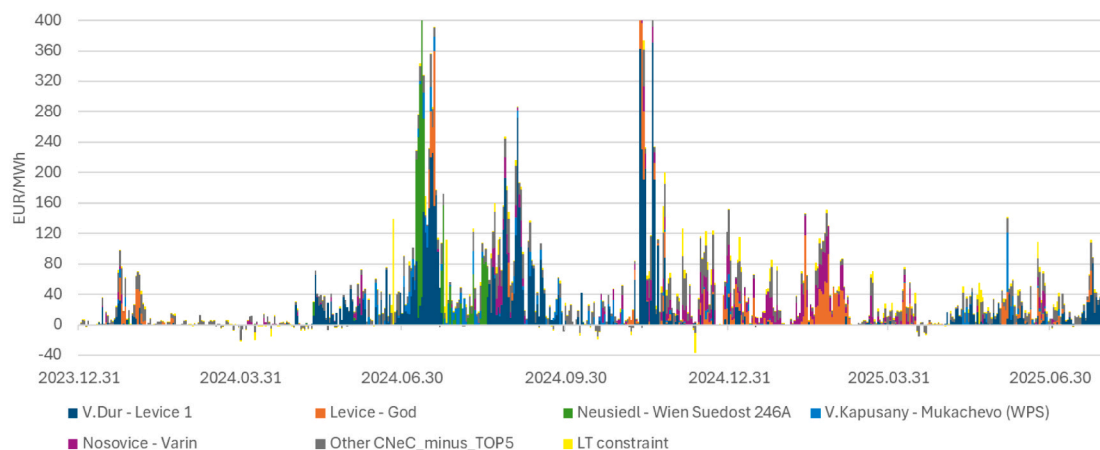


Fig. 6. Average daily DE-HU price difference caused by a given network element

Source: REKK calculation based on JAO database.

High-Price Region, and (2) the difference between the German and Hungarian DAM prices. Hungary was selected because it consistently exhibits some of the largest price spreads relative to Germany during the most critical hours, providing a conservative test of whether the weighted regional average masks local price extremes. The estimated

coefficients remain qualitatively unchanged, indicating that the main results are not driven by averaging across the countries of the High-Price Region.

For each dependent variable, we first estimate a baseline model including consumption, electricity generation, and RAM variables. We

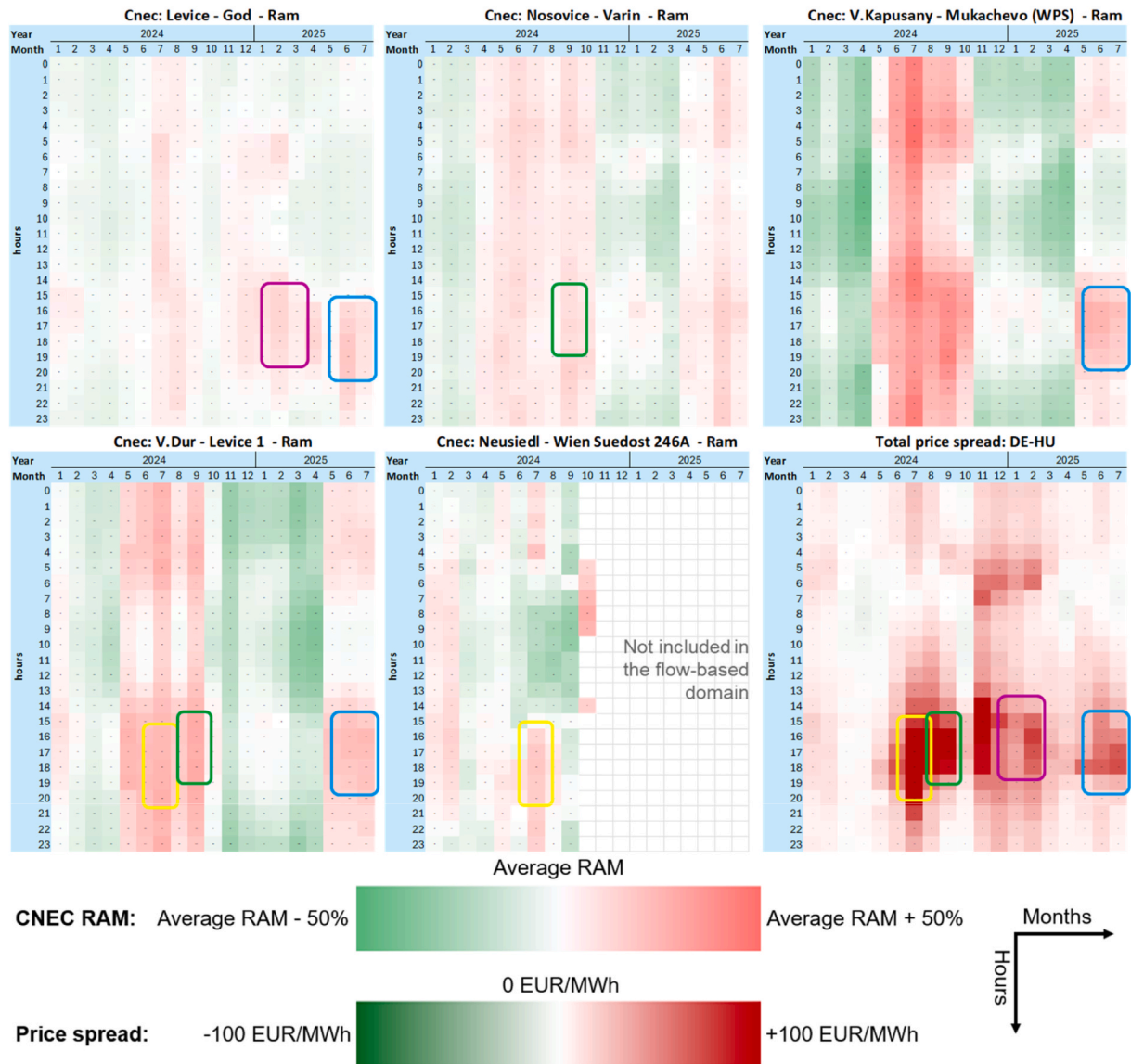


Fig. 7. The development and co-movement of critical network elements' RAM values and the Hungarian-German price difference
Source: REKK calculation based on JAO database.

then perform two robustness checks. First, we estimate an extended specification that additionally controls for the daily TTF gas price to account for the effect of fuel price fluctuations on electricity price differences. Second, we re-estimate the models for a restricted high-price period spanning from 31 March 2024 to 1 April 2025, when price divergence between Germany and the High-Price Region was particularly pronounced. This allows us to assess whether the relationship between transmission constraints and price divergence becomes stronger during periods of sustained market stress.

The three model specifications take the form of the following equations:

$$Y_t = \beta_0 + \beta_1 * Load_Regional_t + \beta_2 * PV_Regional_t + \beta_3 * Wind_Regional_t + \beta_4 * Nuclear_Regional_t + \beta_5 * Hydro_Regional_t + \beta_6 * DAM_DE_t + \beta_7 * DE_VRES_t + \beta_8 * Levice_God_RAM_t + \beta_9 * Dur_Levice_RAM_t + \beta_{10} * Nosovice_Varin_RAM_t$$

(1)

Table 2

Price difference and RAM development when the critical network elements represent an active constraint and when they do not in July 2024.

2024 July	DE-HU Price spread (EUR/MWh)	Dur-Levice 1 RAM (MW)
Active FB constraint average	118	500
No constraint average	43	637
2024 July	DE-HU Price spread (EUR/MWh)	Neusiedl-Wien RAM (MW)
Active FB constraint average	265	158
No constraint average	38	211

Source: REKK calculation based on JAO database

Table 3

RAM factor values for the most critical network elements.

	V.Dur - Levice 1	Levice - God	Neusiedl - Wien Suedost 246A	V.Kapusany - Mukachevo (WPS)	Nosovice - Varin
MinRam Factor	50%	70%	40%	70%	70%
Calculated RAM Factor: active constraint	49%	63%	60%	85%	81%
Calculated RAM Factor: no constraint	52%	69%	68%	88%	81%

Source: REKK calculation based on JAO database

Table 4

Definition and source of independent variables.

Name	Definition	Source
<i>Dependent variables</i>		
<i>Region_DE_PS_weighted_t</i>	difference between the DAM price in Germany and the weighted average of DAM prices in the High-price Region in hour t, with the hourly national load values serving as weights [EUR/MWh]	ENTSO-E Transparency Platform
<i>HU_DE_PS_t</i>	difference between the DAM price in Germany and the DAM price in Hungary in hour t, [EUR/MWh]	
<i>Explanatory variables</i>		
<i>Load_Regional_t</i>	total electricity consumption in the High-Price Region in hour t, [MWh]	ENTSO-E Transparency Platform
<i>PV_Regional_t</i>	PV generation in the High-Price Region in hour t, [MWh]	
<i>Wind_Regional_t</i>	wind energy generation in the High-Price Region in hour t, [MWh]	
<i>Hydro_Regional_t</i>	hydro electricity generation in the High-Price Region in hour t, [MWh]	
<i>Nuclear_Regional_t</i>	nuclear electricity generation in the High-Price Region in hour t, [MWh]	
<i>DE_VRES_t</i>	weather-dependent (wind plus solar) renewable generation in Germany in hour t, [MWh]	EEX ^a
<i>TTF_gas_price_t</i>	day-ahead daily closing price at the Dutch Title Transfer Facility assigned to all hours of the corresponding delivery day to match the hourly resolution of data, [EUR/MWh]	
<i>Levice_God_RAM_t</i>	the RAM values of the considered critical network elements included in the FB domain in hour t [MW]	JAO database
<i>Dur_Levice_RAM_t</i>		
<i>Nosovice_Varin_RAM_t</i>		
<i>Neusiedl_Wien_RAM_t</i>		
<i>D_Neusiedl_Wien_t</i>	Dummy variable indicating the inclusion of Neusiedl-Wien CNEC in the FB domain in hour t	

^a Source: EEX Neutral Gas Price TTF (NGP TTF) – History, available at: <https://www.eex.com/en/market-data/market-data-hub/natural-gas/indices>, REKK data collection, last accessed: 2026.05.02.

$$\begin{aligned}
Y_t = & \beta_0 + \beta_1 * Load_Regional_t + \beta_2 * PV_Regional_t + \beta_3 \\
& * Wind_Regional_t + \beta_4 * Nuclear_Regional_t + \beta_5 * Hydro_Regional_t \\
& + \beta_6 * DAM_DE_t + \beta_7 * DE_VRES_t + \beta_8 * TTF_gas_price_t + \beta_9 \\
& * Levice_God_RAM_t + \beta_{10} * Dur_Levice_RAM_t + \beta_{11} \\
& * Nosovice_Varin_RAM_t
\end{aligned}
\quad (2)$$

$$\begin{aligned}
Y_t = & \beta_0 + \beta_1 * Load_Regional_t + \beta_2 * PV_Regional_t + \beta_3 \\
& * Wind_Regional_t + \beta_4 * Nuclear_Regional_t + \beta_5 * Hydro_Regional_t \\
& + \beta_6 * DAM_DE_t + \beta_7 * DE_VRES_t + \beta_8 * Levice_God_RAM_t + \beta_9 \\
& * Dur_Levice_RAM_t + \beta_{10} * D_Neusiedl_Wien_t + \beta_{11} \\
& * Neusiedl_Wien_RAM_t
\end{aligned}
\quad (3)$$

where Y_t is the dependent variable and t indexes hours.⁷

The explanatory variables included in the models and their sources are presented in Table 4.

5.2. Regression results and discussion

The most relevant network elements (CNECs) for the analysis are the Nosovice–Varín, V. Ďur–Levice and Levice–Göd lines as demonstrated in the CNEC analysis. The other important network elements discussed above, the Neusiedl–Wien Südost and V. Kapusany–Mukachevo lines, were excluded from regressions (1)–(4) and (1)–(6), respectively. The

former was omitted due to its infrequent inclusion in the flow-based domain as a critical network element, while the latter was excluded because of its location at the border of the Core Region.

Table 5 provides a summary of the data for the analysed period, considering the hours when the relevant critical network elements were included in the flow-based domain. The number of observations is 12,726 for all variables. The mean price difference between the regional average DAM and the German DAM was 20.7 EUR/MWh, while the median was 7.1 EUR/MWh. The spread between Hungarian and German prices was somewhat higher on average but exhibited a lower median value. In both cases, the coefficient of variation exceeded 2, indicating substantial dispersion around the central values. The distributions were also strongly right-skewed, as reflected in the large differences between median and maximum values.

The region's mean hourly total load is around 27–28 GWh, and the average electricity production from the sources included in the models ranges from 2.6 GWh for wind to 4.7 GWh for nuclear, with nuclear showing the lowest variability. On average, Germany's total VRES generation (PV plus wind) is more than three times the region's combined PV and wind production. As regards the analysed network elements, their RAM varies widely, with a range exceeding 1000 MW as indicated by the minimum and maximum values.

The regression results are summarised in Table 6. Models (1)–(4) present the baseline and gas-price specifications estimated for the full sample, while Models (5)–(6) report the results for the restricted high-price period (31 March 2024–1 April 2025). Overall, the estimated coefficients remain remarkably stable across specifications, indicating that the main findings are robust to both the inclusion of gas prices and the restriction of the sample to the period of sustained market stress. Adjusted R^2 values range from approximately 0.24 to 0.33. The highest explanatory power is obtained for the regional price spread during the restricted high-price period, suggesting that the selected explanatory variables capture the drivers of price divergence particularly well during periods of persistent market stress. While the results vary slightly across model specifications, they remain robust with respect to the main

⁷ Please note that in the high-price period for which specification (3) was tested, the RAM for the Neusiedl-Wien network element equals zero for a substantial share of observations (87%); therefore, we include a dummy variable ($D_Neusiedl_Wien_t$) equal to one when $RAM > 0$ alongside the RAM itself, rather than treating $Neusiedl_Wien_RAM_t$ as a single continuous regressor to avoid bias in the estimated coefficients.

Table 5
Descriptive statistics of the variables.

	Mean	Median	Minimum	Maximum	Std. Deviation
<i>Region_DE_PS_weighted (EUR/MWh)</i>	20.64	7.09	−263.79	631.19	47.24
<i>HU_DE_PS (EUR/MWh)</i>	21.11	4.96	−157.12	773.50	53.41
<i>Load_Regional (MWh)</i>	27724.18	27482.60	16653.67	40265.20	4633.97
<i>PV_Regional (MWh)</i>	3585.41	275.08	0.00	20899.58	4888.75
<i>Wind_Regional (MWh)</i>	2603.62	2377.91	75.24	8054.61	1373.50
<i>Nuclear_Regional (MWh)</i>	4659.12	4954.40	2878.25	5467.57	672.61
<i>Hydro_Regional (MWh)</i>	4103.69	3714.41	799.25	9600.99	1812.74
<i>DE_VRES (MWh)</i>	23065.25	21451.79	129.43	66306.29	13769.32
<i>TTF_gas_price (EUR/MWh)</i>	36.64	35.29	23.04	58.31	7.37
<i>Levice_God_RAM (MW)</i>	870.98	890.00	343.00	1726.00	82.37
<i>Dur_Levice_RAM (MW)</i>	776.10	776.00	230.00	1311.00	150.71
<i>Nosovice_Varin_RAM (MW)</i>	969.91	965.00	402.00	1623.50	137.13
<i>Neusiedl_Wien_RAM (MW)</i>	35.16	0.00	0.00	368.00	78.01
<i>D_Neusiedl_Wien</i>	0.17	0.00	0.00	1.00	0.38

Note: N=12,726.

Table 6
Results of the regression analysis.

REGRESSION MODEL	(1)	(2)	(3)	(4)	(5)	(6)
DEPENDENT VARIABLE	Price diff. between DE and the Region (EUR/MWh)	Price diff. between DE and HU (EUR/MWh)	Price diff. between DE and the Region (EUR/MWh)	Price diff. between DE and HU (EUR/MWh)	Price diff. between DE and the Region (EUR/MWh)	Price diff. between DE and HU (EUR/MWh)
Observations	12,726	12,726	12,726	12,726	7878	7878
R-squared	0.3019	0.2403	0.3026	0.2417	0.3308	0.2856
Adjusted R-squared	0.3015	0.2398	0.3020	0.2411	0.3300	0.2847
COEFFICIENTS						
Load_Regional (MWh)	0.00411***	0.00479***	0.00388***	0.00440***	0.00452***	0.00549***
PV_Regional (MWh)	−0.00520***	−0.00458***	−0.00507***	−0.00436***	−0.00643***	−0.00595***
Wind_Regional (MWh)	−0.00733***	−0.00681***	−0.00725***	−0.00667***	−0.00804***	−0.00814***
Nuclear_Regional (MWh)	−0.00820***	−0.00589***	−0.00783***	−0.00528***	−0.00856***	−0.00462*
Hydro_Regional (MWh)	−0.00274***	−0.00207***	−0.00214***	−0.00108*	−0.000150	0.00106
DE_VRES (MWh)	0.00117***	0.00076***	0.00119***	0.00079***	0.00160***	0.00119***
TTF_gas_price (EUR/MWh)			0.227	0.375**		
Levice_God_RAM (MW)	−0.0312***	−0.0354***	−0.0285***	−0.0310**	−0.0319*	−0.0347*
Dur_Levice_RAM (MW)	−0.0209**	−0.0164	−0.0241**	−0.0218*	−0.0352***	−0.0280**
Nosovice_Varin_RAM (MW)	−0.0212***	−0.0268***	−0.0208***	−0.0261***		
D_Neusiedl_Wien (dummy)					37.74	121.0**
Neusiedl_Wien:RAM (MW)					−0.176	−0.558**
Constant	30.83**	10.62	23.56*	−1.38	2.407	−42.46

Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.

Source: REKK calculation based on JAO database, ENTSO-E Transparency Platform

variables as shown in Table 6.

The estimated coefficients indicate a highly significant relationship between the explanatory variables and the price differentials. Higher regional electricity consumption is associated with a larger price difference. Based on Regressions 1 and 2, a 1000 MWh (1 GWh) increase in regional load results in a 4.1 EUR/MWh increase in the regional price spread and a 4.8 EUR/MWh increase in the Hungary–Germany price differential.

The coefficients estimated for the various generation sources indicate that higher production levels reduce price differences. For example, based on Regression 1, a 1000 MWh (1 GWh) increase in PV, wind, nuclear, and hydro generation in the Region reduces the price spread by 5.2, 7.3, 8.2, and 2.7 EUR/MWh, respectively, while in Hungary (Regression 2) the effects are somewhat smaller.

The coefficient on German renewable generation is positive in all specifications, indicating that a 1000 MWh (1 GWh) increase in RES generation in Germany is associated with a widening of the regional price spread by approximately 1.2 EUR/MWh and of the Hungarian price differential by about 0.8 EUR/MWh.

Regarding the TTF gas price, no significant relationship is found with the regional price difference (Regression 3). However, it has a statistically significant effect on the Hungarian price difference: a 1 EUR/MWh increase in the TTF gas price resulted in a 0.375 EUR/MWh increase in the spread, as shown by the results of Regression 4. Importantly, controlling for gas prices has no significant effect on the estimated coefficients of the remaining explanatory variables, confirming that the main results are not driven by fluctuations in fuel prices.

The RAM coefficients remain negative across all specifications, suggesting that transmission capacity constraints play a significant role in price convergence between Germany and the High-Price Region. In the full-sample regressions, the Levice–Göd, V. Ďur–Levice and Nosovice–Varin CNECs are all associated with statistically significant reductions in price differences as available RAM increases. Based on Regression 1, a 100 MW increase in RAM for the critical network elements reduces price differences by 3.1 EUR/MWh for the Levice–Göd line, 2.1 EUR/MWh for the V. Ďur–Levice line, and 2.1 EUR/MWh for the Nosovice–Varin line. For the Hungarian price spread (Regression 2), the corresponding effects are 3.5, 1.6, and 2.7 EUR/MWh, respectively.

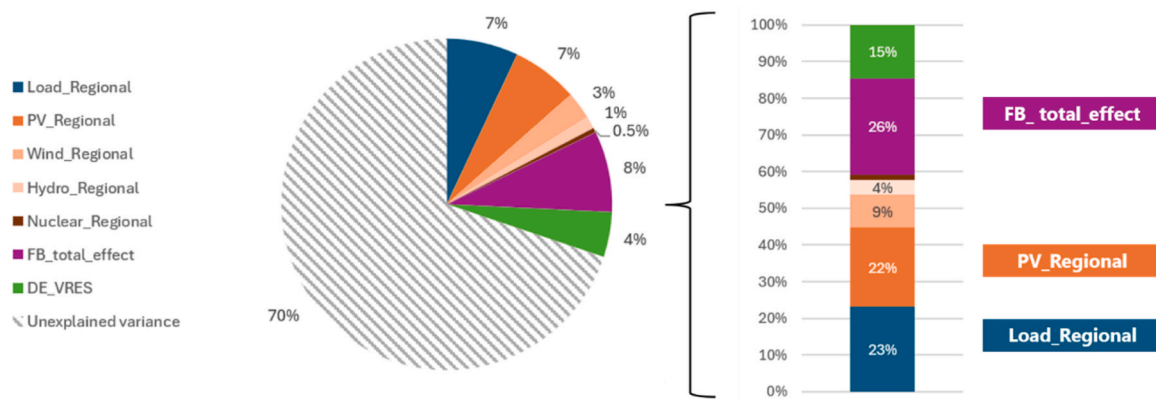


Fig. 8. The relative importance of the explanatory variables (entire period)
Source: REKK calculation.

Restricting the analysis to the high-price period reveals that the overall importance of transmission constraints remains unchanged, but the relative importance of individual CNECs shifts (Regressions 5 and 6). While the effect of the Levice–Göd line remains broadly unchanged, the coefficient of the V. Ďur–Levice line becomes substantially larger in absolute value, indicating that this constraint played a more pronounced role during periods of sustained market stress. By contrast, the Nosovice–Varín line is no longer statistically significant and is therefore excluded from Models (5) and (6). Instead, the Neusiedl–Wien CNEC becomes highly significant for the Hungarian price spread, suggesting that congestion within the Austrian transmission network became particularly important in this period.

The model's overall fit, measured by the R^2 value, was above 30% in case of Regressions 1, 3, and 5, which focused on the regional price spread. This suggests that the included variables explained around a third of the variation in price differences. Fig. 8 illustrates the contribution of the independent variables in explaining the observed price difference in case of Regression 1. Of the 30.3% variance explained by the model, the most significant contributors were RAM values across the three evaluated network elements (26%), regional load (23%) and photovoltaic (PV) generation within the High-Price Region (22%).

6. Conclusions and policy implications

The persistent price divergence between Central and South-Eastern Europe is the result of the combined effect of the regional consumption patterns, the supply characteristics, and the transmission bottlenecks. While the flow-based market coupling framework has improved the overall European efficiency, its benefits remain unevenly distributed: the High-Price Region faces systematically higher wholesale prices, driven not only by cross-border constraints but also by internal grid limitations that now shape regional price formation. Despite its welfare-maximising intent, the flow-based system often operates as a “black box” for market participants. Compared with the previous NTC-based allocation method, the FBMC's complexity and limited transparency make it difficult for stakeholders to interpret or anticipate the market outcomes. Improved transparency in the calculation of RAM and earlier disclosure of RAM values would help market participants better understand and forecast sudden RAM swings and congestion patterns.

Furthermore, enforcement of the 70% minimum RAM rule must be prioritised where it matters most. Compliance is particularly critical on high-impact CNECs such as V. Ďur–Levice and Neusiedl–Wien, which have a disproportionate influence on regional price spreads. This finding leads to the same conclusion as Nagy et al. (2025), that single line bottlenecks can cause high price differences amongst neighbouring countries of the Core region. Targeted monitoring by ACER and ENTSO-E, combined with transparent penalties for non-compliance

would ensure consistent application of the rule and strengthen confidence in the FBMC system.

The 5% PTDF threshold used for CNEC selection represents an important modelling choice within the FBMC framework. While the present analysis does not directly quantify the impact of this threshold, our results suggest that the criteria governing the inclusion of constraints in the flow-based domain may be economically relevant. In particular, we find that some CNECs that are included in the domain only during a limited number of hours can nevertheless generate disproportionately large price effects when they become binding. This indicates that relatively small changes in the CNEC selection criteria – including the PTDF threshold – may influence market outcomes through the intermittent inclusion or exclusion of high-impact constraints. Further research could explicitly investigate the sensitivity of market outcomes to alternative PTDF thresholds and CNEC selection methodologies.

Economic incentives for internal grid reinforcement should also be reconsidered. Current arrangements create an investment incentive gap: while internal CNECs often deliver cross-border benefits, their upgrade costs are borne nationally. A European-level cost-sharing or compensation mechanism would help ensure that countries hosting critical internal bottlenecks are incentivised to make investments primarily enhancing regional welfare. In parallel, PCI and PMI selection processes of the current EU planning framework under the TEN-E Regulation (European Commission, 2022) should prioritise true welfare bottlenecks, ranking candidate projects based on persistent shadow prices, measured welfare losses, and their potential to reduce structural price spreads. As the FBMC methodology offers all parameters necessary for welfare optimisation, EU infrastructure policy should be revisited to incorporate the valuable insights these calculations provide. This alignment is further supported by the proposed EU Grid Package (European Commission, 2025), which seeks to ensure a seamless coordination across national, regional and EU governance levels. Finally, enhancing system flexibility is crucial to mitigate the effects of binding constraints. Storage (particularly batteries) and demand-side response (DSR) should be incentivised to provide peak-hour relief when flow-based limits are most restrictive. Dynamic or time-of-use tariffs could encourage consumers to shift demand away from the 17:00–21:00 peak window, easing network congestion and improving welfare. Fast, flexible generation capacity – including hybrid wind-plus-storage solutions – can complement these measures, providing cost-effective coverage during high-stress hours.

CRedit authorship contribution statement

Adrienn Selei: Writing – original draft, Validation, Methodology, Conceptualization, Writing – review & editing. **Gábor Horváth:**

Visualization, Investigation, Data curation, Writing – review & editing. **András Mezősi:** Writing – original draft, Validation, Investigation, Conceptualization. **Mária Bartek-Lesi:** Writing – original draft, Methodology, Investigation, Writing – review & editing. **László Szabó:** Writing – original draft, Validation, Conceptualization.

Declaration of competing interests

The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A.1

Pairwise correlation matrix of electricity price spreads relative to Germany used for identifying the High-Price Region

	HU	HR	RO	BG	RS	GR	SK	SI	PL	CZ	AT	BE	FR	NL	CH	IT	ES	PT	DK	SE	NO	FI	EE	LT	LV
HU	1.00																								
HR	0.85	1.00																							
RO	0.90	0.84	1.00																						
BG	0.87	0.83	0.98	1.00																					
RS	0.78	0.76	0.83	0.82	1.00																				
GR	0.71	0.72	0.80	0.82	0.80	1.00																			
SK	0.75	0.77	0.68	0.69	0.63	0.60	1.00																		
SI	0.66	0.88	0.68	0.69	0.66	0.64	0.72	1.00																	
PL	0.43	0.45	0.46	0.45	0.54	0.55	0.41	0.38	1.00																
CZ	0.24	0.44	0.23	0.24	0.24	0.25	0.53	0.55	0.19	1.00															
AT	0.21	0.36	0.22	0.25	0.33	0.31	0.49	0.43	0.17	0.67	1.00														
BE	−0.02	0.09	−0.01	0.01	0.11	0.18	0.16	0.14	0.08	0.25	0.46	1.00													
FR	0.01	0.10	0.02	0.04	0.18	0.24	0.16	0.14	0.17	0.20	0.48	0.85	1.00												
NL	0.04	0.09	0.03	0.04	0.03	0.10	0.14	0.14	−0.05	0.26	0.24	0.62	0.37	1.00											
CH	−0.01	0.10	−0.02	0.01	0.17	0.21	0.23	0.17	0.17	0.42	0.73	0.62	0.65	0.26	1.00										
IT	0.14	0.28	0.19	0.21	0.41	0.50	0.29	0.31	0.44	0.34	0.55	0.50	0.58	0.23	0.63	1.00									
ES	0.06	0.17	0.09	0.12	0.28	0.33	0.21	0.19	0.24	0.25	0.46	0.56	0.69	0.26	0.49	0.65	1.00								
PT	0.06	0.17	0.10	0.12	0.28	0.34	0.21	0.20	0.25	0.26	0.47	0.56	0.68	0.25	0.49	0.66	1.00	1.00							
DK	−0.06	−0.07	−0.07	−0.06	−0.11	−0.03	−0.10	−0.07	0.04	−0.03	−0.07	0.02	0.02	0.09	−0.03	0.04	−0.06	−0.06	1.00						
SE	−0.14	−0.06	−0.12	−0.10	0.01	0.07	−0.03	−0.02	0.24	0.13	0.29	0.37	0.43	0.15	0.47	0.51	0.25	0.25	0.39	1.00					
NO	−0.18	−0.08	−0.16	−0.14	0.00	0.11	−0.04	−0.04	0.27	0.14	0.30	0.44	0.49	0.20	0.52	0.63	0.36	0.36	0.34	0.91	1.00				
FI	−0.09	−0.04	−0.09	−0.08	0.03	0.08	−0.02	−0.01	0.23	0.09	0.20	0.27	0.29	0.10	0.34	0.38	0.18	0.19	0.25	0.72	0.64	1.00			
EE	0.16	0.19	0.16	0.16	0.18	0.22	0.17	0.19	0.35	0.10	0.10	0.07	0.10	0.00	0.08	0.22	0.08	0.08	0.20	0.37	0.28	0.70	1.00		
LT	0.19	0.23	0.18	0.18	0.20	0.24	0.20	0.22	0.39	0.12	0.10	0.05	0.09	−0.01	0.06	0.22	0.07	0.08	0.20	0.35	0.26	0.61	0.94	1.00	
LV	0.19	0.23	0.19	0.19	0.21	0.25	0.20	0.22	0.39	0.12	0.11	0.06	0.10	0.00	0.07	0.23	0.08	0.09	0.20	0.35	0.27	0.61	0.94	1.00	1.00

Data availability

Data will be made available on request.

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