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AUTHOR

Markos Farag

Oliver Ruhnau

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Institute of Energy Economics at the University of Cologne (EWI)

www.ewi.uni-koeln.de

Institute of Energy Economics
at the University of Cologne (EWI)

Alte Wagenfabrik
Vogelsanger Str. 321a
50827 Köln
Germany

Tel.: +49 (0)221 277 29-100
Fax: +49 (0)221 277 29-400
www.ewi.uni-koeln.de

CORRESPONDING AUTHOR

Markos Farag
mfarag1@uni-koeln.de

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Decomposing Return and Volatility Connectedness in Northwest European Gas Markets: Evidence from the R^2 connectedness approach

Markos Farag[a,*], Oliver Ruhnau[a,b]

[a] *Faculty of Management, Economics and Social Sciences, University of Cologne, Universitätsstraße 24a, 50931 Cologne, Germany*

[b] *Institute of Energy Economics at the University of Cologne, Vogelsanger Str. 321a, 50827 Cologne, Germany*

Abstract

Regulatory reforms by the European Commission have facilitated the integration of the European gas market, increasing interdependence in prices and associated risks across gas hubs. Recent external shocks, including the COVID-19 pandemic and the Russian invasion of Ukraine, have disrupted market interconnectedness, as evidenced in the literature. However, whether the nature of shock transmission—contemporaneous or delayed—changes during market instability, how quickly price and volatility connectedness recover afterward, and whether spot and futures prices are affected differently remain unclear. This paper analyzes the connectedness of natural gas hubs in Northwest Europe from 2020 to 2024 using the R^2 decomposition connectedness method. Our findings show that contemporaneous spillovers dominate lagged ones, even during external shocks, indicating rapid market adjustments. Moreover, while market connectedness significantly decreased during major disruptions, it promptly returned to pre-crisis levels once these disruptions subsided. Regression results indicate a significant link between reduced market connectedness and pipeline congestion, particularly when combined with higher future price expectations. Futures markets showed higher connectedness than spot markets during tight conditions, suggesting alignment with broader expectations and reduced susceptibility to physical constraints.

Keywords: European Natural gas market; Dynamic linkages; R^2 decomposition; volatility

JEL classification: C11; C32; F14; L71; Q31; Q43.

* Corresponding author

Email address: `mfarag1@uni-koeln.de` (Markos Farag)

1. Introduction

The European Commission has prioritized the creation of an integrated gas market to ensure affordable and stable gas supplies for customers across Europe (Brons et al., 2019). To achieve this, several regulatory reforms, such as Directive 2009/73/EC, have been implemented to remove market barriers, enhance regulatory oversight, and improve market integration and transparency. These measures have facilitated the transition to hub trading and gas-on-gas pricing within the European gas market (Bianco et al., 2015; Garaffa et al., 2019). The observed interdependence in price changes (return connectedness) and the associated risks (volatility connectedness) across these gas hubs underscores the extent of market connectedness (Broadstock et al., 2020). Such interdependence enhances overall welfare by fostering competition, reducing price disparities, and promoting efficient resource allocation (Gugler et al., 2018; Anderson and Ginsburgh, 1999).[1]

However, recent years have seen extreme external factors, such as the COVID-19 pandemic and the Russian invasion of Ukraine, significantly impacting wholesale prices and trading environments (see Heather (2022, 2024) for a detailed analysis). Previous studies by Chen et al. (2022) and Szafranek et al. (2023) have demonstrated that these shocks also led to reduced market connectedness in terms of price returns between gas hubs. Building on this prior analysis, this paper extends the study of connectedness by addressing the following research questions: *Do European gas markets influence each other's price returns and volatility contemporaneously, or are there delays in this transmission?; How does the timing of connectedness vary between tight and stable market conditions?; How quickly does connectedness recover following major disruptions?*

This paper employs the R^2 decomposition connectedness method, recently introduced by Balli et al. (2023), to analyze return and volatility connectedness among European natural gas benchmarks. Specifically, it focuses on the connectedness of spot prices from four Northwest European (NWE) natural gas hubs: the Title Transfer Facility (TTF) in the Netherlands, the National Balancing Point (NBP) in the United Kingdom, Trading Hub Europe (THE) in Germany, and the Zeebrugge Trading Point (ZTP) in Belgium, over the period from 2020 to 2024.[2] Moreover, we examine the connectedness of futures prices to capture how expectations and forward-looking information are shared among markets. Finally, we conduct a regression analysis to identify the factors associated with the connectedness of the NWE gas markets, focusing on key economic and structural aspects such as pipeline congestion and market expectations. In doing so, this study aims to contribute to the literature on European gas market integration, as reviewed in detail in Section 2, in three ways:

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[1] Note that the costs of increasing market connectedness (e.g., the costs of extending pipeline infrastructure) should be considered when evaluating (net) welfare gains. Furthermore, increasing market connectedness may involve distributional effects. Specifically, price convergence can reduce consumer surplus in regions that initially had lower prices, whereas consumers in previously high-price regions benefit (Finon and Romano, 2009).

[2] These four benchmarks are the focus of the analysis as they represent the NWE gas market, which is expected to exhibit closer market fundamentals and shorter transportation distances due to regional proximity.

First, we apply the R^2 connectedness framework to decompose spillover effects among gas benchmarks into contemporaneous and lagged components. While previous studies, such as those by Broadstock et al. (2020) and Chen et al. (2022), have explored transmission mechanisms within European gas markets, they did not differentiate between immediate and delayed spillovers. This distinction in our work provides novel insights, helping market participants determine whether to respond swiftly to shocks or prepare for more gradual impacts, thereby enhancing risk management and optimizing hedging strategies. Additionally, the R^2 decomposition approach is computationally more efficient than the connectedness methodologies proposed by Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014), as it avoids the associated normalization problem.[3]

Second, by examining the period from 2020 to 2024, we extend existing analyses of market connectedness during the COVID-19 pandemic and the 2021-22 energy crisis by also investigating post-crisis recovery. Since 2023, the expansion of LNG infrastructure and reductions in demand have led to the stabilization of European natural gas prices (ACER, 2023a; Ruhnau et al., 2023). Therefore, our examination period captures not only the immediate disruptions caused by the COVID-19 pandemic and the Russian invasion of Ukraine but, more importantly, the speed and effectiveness of the subsequent recovery of European gas markets and the re-establishment of market connectedness following these events. This provides a comprehensive understanding of the market's resilience and the pace at which connectedness is restored after major disruptions. Furthermore, we differentiate between spot and futures prices to examine how their connectedness levels vary across periods of market tightness and stability, providing insights into the differing roles of short-term dynamics versus market expectations.

Lastly, we conduct a regression analysis to identify the factors associated with the level of connectedness in the NWE gas markets. Specifically, we assess the relationship between market connectedness and various factors, including physical constraints such as infrastructure congestion between the UK and other NWE countries, market expectations, geopolitical factors, and the 2022 storage mandate implemented during the energy crisis. This analysis helps us understand how these diverse drivers shape the dynamics of gas market connectedness.

The findings of this study can be summarized as follows. In terms of total return connectedness, we observe a slight reduction during the COVID-19 pandemic and a sharp decline from the second quarter of 2022, following the Russian invasion of Ukraine, which is consistent with previous studies (Papież et al., 2022; Chen et al., 2022). Our analysis of the extended sample through 2024 reveals that recovery began in mid-2023, with market connectedness reaching pre-crisis levels by year-end. Total volatility connectedness followed a similar, though slightly less pronounced, trajectory. Our comparative connectedness analysis of spot and futures prices reveals that futures markets exhibited higher connectedness than spot markets during

[3] For further details on how this approach addresses the normalization problem, see Section 4.

periods of stress, indicating that they were less impacted by physical constraints and more aligned with broader market expectations.

Decomposing the total connectedness index reveals that contemporaneous effects consistently dominate lagged effects for both return and volatility connectedness. This suggests that market participants respond quickly to new information, and price adjustments among gas hubs occur immediately. The persistence of contemporaneous effects during both tight and stable market conditions indicates that the speed of information transmission and market response remains unaffected by shifts in market conditions. This consistent response can be attributed to advanced trading mechanisms and financial instruments, such as virtual trades, locational swaps, and derivatives, which facilitate rapid information flow and immediate price adjustments across varying market conditions (ACER, 2023b).

Our directional analysis shows that the connectedness of NBP and ZTP with TTF and THE dropped significantly during disruptions, with NBP even decoupling completely in late 2022. TTF typically acted as a net transmitter of shocks but became a net receiver from late 2022 to late 2023, while THE transitioned to being a net transmitter during this period, potentially due to increased spot trading linked to Germany's need to replace Russian gas and the expansion of LNG infrastructure. NBP consistently remained a net receiver. The results also indicate that TTF exhibits a close alignment between contemporaneous and overall net spillover effects, reflecting its immediate influence on other hubs, as its shocks are transmitted to them without delay, often on the same day, likely due to its high liquidity and active trading. This finding is consistent with Liu et al. (2024), suggesting that markets with substantial liquidity tend to be highly influenced by contemporaneous factors.

Finally, our regression analysis reveals significant associations between reduced connectedness and congestion in the pipelines connecting the UK with Belgium and the Netherlands. When combined with futures spreads, the negative association between congestion and connectedness intensifies, suggesting that higher futures spreads exacerbate market decoupling amid congestion. We also find that the EU storage mandate to fill gas storage to 80% capacity is associated with a reduction in market connectedness, indicating that varying storage obligations may have contributed to decreased interdependence among NWE markets. Lastly, higher geopolitical risk is correlated with increased connectedness, likely due to shared market responses to geopolitical events.

The implications of these results are as follows: The dominance of contemporaneous spillovers indicates that these markets adjust almost immediately to shocks. This rapid adjustment requires constant monitoring and quick decision-making by market participants to effectively manage increased volatility risks. The observed decrease in connectedness during crises, along with its association with pipeline congestion, suggests that physical infrastructure constraints can significantly disrupt market integration. However, this effect appears temporary, as connectedness tends to recover once these constraints are alleviated. This implies that, while infrastructure enhancements could increase market efficiency, caution is needed to avoid overinvesting in potentially redundant capacity after markets have recovered.

The rest of the paper is structured as follows: Section 2 reviews the literature on European gas market integration. Section 3 describes the data used, including their sources, and outlines the dynamics in the NWE gas markets. Section 4 discusses the methodology employed in the analysis, while Section 5 presents the results of the connectedness analyses. Section 6 examines the factors associated with this connectedness. Finally, Section 7 concludes the study.

2. Literature review

The integration of natural gas markets has been central to European gas market liberalization. The liberalization process began with the First Gas Directive in 1998 (Directive 98/30/EC), which introduced competition and established common rules, including non-discriminatory rights for building new gas infrastructure. This was followed by the Second Gas Directive in 2003 (Directive 2003/55/EC), which mandated the unbundling of gas operators to separate transport networks from production and supply, thereby broadening consumer choice. Despite these reforms, the market continued to face significant hurdles such as concentration, vertical integration, and cross-border trade barriers. This prompted the European Commission to conduct the 'DG Competition Report on Energy Sector Inquiry' in 2007, which identified key areas lacking effective competition. In response, the Third Energy Package was enacted in 2009, including Directive 2009/73/EC, which focused on establishing common rules for the internal market in natural gas and repealed Directive 2003/55/EC. This package aimed to further dismantle market barriers, improve regulatory oversight, and enhance market integration and transparency (Bianco et al., 2015; Demir and Demir, 2020). These legislative efforts have gradually reshaped the European natural gas market, promoting a more integrated and competitive environment, which is crucial for the convergence of gas prices across Europe. Such significant changes naturally raise questions about the effectiveness of these liberalization efforts in achieving a truly integrated and competitive market, prompting empirical and academic studies to rigorously examine these issues.

Research on the integration of the European gas market can be categorized into two strands of literature, both primarily utilizing prices from hub-based continental European markets. The first strand focuses on identifying cointegration or convergence among natural gas prices to assess the effectiveness of market integration. The second strand adopts the spillover methodology, also referred to as connectedness, initially developed by Diebold and Yilmaz (2009), which calculates the 'spillover index' to quantify how much of the forecast error variance in one market can be explained by shocks in another. This methodology was further extended by Diebold and Yilmaz (2012) to include both a generalized Vector Autoregression (VAR) structure (i.e., invariant to variable ordering) and directional spillovers (i.e., the 'FROM' and 'TO' analyses).

The connectedness and cointegration approaches differ in both their focus and methodological frameworks when analyzing market integration. The connectedness approach, often based on Vector Autoregression (VAR) models, captures the transmission of shocks between markets by employing forecast error variance decompositions (FEVD). This allows for the measurement of both total and directional spillovers, showing how much of the forecast error variance in one market is explained by innovations in others, in terms of returns or volatility, across different horizons (short-run or long-run), depending on the model and decomposition method used (Diebold and Yilmaz, 2009, 2012; Baruník and Křehlík, 2018; Naeem et al., 2024a). In contrast, the cointegration approach focuses on long-term equilibrium relationships between markets. It examines whether gas prices that do not follow a constant pattern over time tend to move together in the long run due to underlying economic factors, with deviations from this equilibrium being temporary and corrected over time, typically through price adjustments in response to supply-demand imbalances (Alexander and Wyeth, 1994). In this context, while the connectedness approach is useful for understanding market interdependencies and the flow of volatility or return shocks between specific markets, the cointegration approach is better suited for assessing long-term market integration and common trends.

Regarding the first strand of literature, extensive empirical work demonstrates the use of cointegration tests to reveal the degree of market integration. Asche et al. (2002) investigate market integration in the German natural gas market and the impact of long-term take-or-pay contracts. Analyzing 1990–1998 time series data on gas export prices from Norway, the Netherlands, and Russia, the Johansen cointegration test shows proportional price movements, confirming market integration. However, they found that Russian gas prices were systematically lower than Dutch and Norwegian prices, primarily due to differences in volume flexibility, transport costs, and political risk. Growitsch et al. (2015) estimated a time-varying coefficient model to study the convergence path of spot prices in German and Dutch trading hubs. They found improvements in market efficiency and significant price convergence since the introduction of the entry-exit system. Similarly, Neumann and Cullmann (2012) examined price convergence across eight European gas hubs by applying the Kalman filter to estimate time-varying coefficients, which represent the evolution of market integration over time. Their analysis revealed that only twelve out of twenty-eight possible price pairs exhibited significant integration, with varying degrees of convergence over time. The results also highlighted that market integration fluctuates seasonally, with lower levels of convergence during the winter months, when natural gas prices tend to rise due to higher demand. Accounting for non-linear adjustments between regional European markets, Garaffa et al. (2019) examined price transmission dynamics between the German, Belgian, and Dutch spot markets from April 2013 to December 2014. Their analysis confirmed cointegration and identified significant price asymmetries, particularly in the German market, where transaction costs were evident. Further studies have applied convergence methods to analyze the integration of the European gas market. Robinson (2007) employed convergence tests to analyze annual retail natural gas prices for six EU Member States—Finland, France, Ireland, the Netherlands, Spain, and the UK—from 1978 to 2003. The results indicate some evidence of price convergence according to the β-convergence [4] and Bernard-Durlauf tests. Moreover, Bastianin et al. (2019) extended the analysis to fourteen European countries from 1991 to 2017 using natural gas prices for industrial consumers. Their analysis provides evidence of pairwise, σ-convergence[5], and relative price convergence, which is closely linked to the presence of trading hubs and market interconnections.

Moving to the second strand, the focus shifts to the dynamics of price spillovers, exploring how connectedness influences market behavior. Broadstock et al. (2020) employ the spillover methodology, particularly the framework developed by Diebold and Yilmaz (2009), to assess the integration of European natural gas markets by examining the connectedness of price returns and volatilities from key trading hubs (NBP, ZEE[6], and TTF). The main findings indicate that while European gas markets show a significant level of integration, with spillover index values between 38% and 69%, complete integration has not yet been achieved. They also find that there has been a notable increase in spillovers since the implementation of the Third Gas Directive in 2009, with TTF emerging as a more dominant hub in terms of both return and volatility spillovers, reflecting its rising importance in the market. Complementing this, Papież et al. (2022) employ the Diebold and Yilmaz (2009) framework combined with a time-varying parameters VAR model with stochastic volatility (TVP-VAR-SV). They focus on the connectedness of daily price changes and weekly realized volatility across four key gas hubs: TTF, NBP, NCG, and PSV, analyzing data from November 2013 to January 2022. Their results show a steady rise in the total spillover index, particularly from mid-2017, underscoring a robust co-movement across these markets. However, their analysis shows that when the COVID-19 pandemic hit, the connectedness index decreased substantially by about 15 percentage points from the initial 60% level. This finding was corroborated by Chen et al. (2022), who used a quantile spillover approach to analyze the integration of the European natural gas futures market, particularly during extreme events. They argue that the declining integration during the pandemic was due to increased market instability, a severe imbalance between supply and demand, and significant disruptions to usual market operations. Further, Szafranek et al. (2023) analyzed price dynamics during the turbulent 2021–2022 period using the frequency decomposition method introduced by Baruník and Křehlík (2018) to examine the connectedness of four major European natural gas hubs. The main result reveals that while the

[4]The *beta*-convergence approach tests whether countries with initially lower gas prices experience faster price growth than those with higher initial prices. The estimate of the rate of convergence, represented by β, indicates how close prices are to converging toward a common level, with a β value close to 1 suggesting absolute convergence.

[5]σ-convergence refers to tracking whether the cross-sectional variance of natural gas prices decreases over time as prices converge across countries. The σ represents the cross-sectional standard deviation of log-prices, which is used to measure the dispersion of prices across countries. A decrease in the cross-sectional standard deviation over time indicates σ-convergence, implying that price differences between countries are shrinking.

[6]ZEE refers to the Zeebrugge Beach gas market, a Belgian gas market that operated alongside the ZTP (Zeebrugge Trading Point). Since 2022, ZEE has experienced a significant decline in trading volumes due to expiring capacity contracts and reduced liquidity, whereas ZTP has attracted more national gas trade (Heather, 2021). To streamline operations, the Belgian regulator approved the merger of the ZEE and ZTP hubs, which took effect on October 1, 2023 (EEX, 2023).

connectedness of European gas markets increased significantly before the Russian invasion of Ukraine, it declined markedly afterward.

The findings from both strands of literature reveal a progressive alignment in gas prices across European hubs, indicative of market integration facilitated by regulatory frameworks such as the entry-exit system and successive EU Gas Directives. However, instances of decreased integration often occur, typically linked to significant disruptive events.

The current study contributes to the literature on connectedness analysis in the European gas market by employing a methodological approach that dissects both contemporaneous and lagged spillover effects across gas benchmarks. In doing so, it extends prior research, which primarily focused on immediate spillover effects, often overlooking the potential for lagged interactions to develop over time. Furthermore, the study examines the period from 2020 to 2024 to investigate how different shocks during this time impacted market connectedness and how connectedness evolved during subsequent recovery and stabilization phases.

3. Dynamics of gas prices and volatility in NWE

The European natural gas market consists of multiple price hubs. This study focuses on the connectedness of gas price hubs in NWE for three main reasons. First, the NWE region accounts for over half of the EU's gas consumption, underscoring its central role in the European gas market (Eurostat, 2023). Second, in 2022, the gas-on-gas pricing mechanism dominated the region, comprising approximately 82% of pricing strategies, highlighting the increasing maturity and liquidity of NWE's gas hubs (IGU, 2022). Finally, gas hubs within the same region are expected to share similar market fundamentals—such as supply sources, demand patterns, and infrastructure—which contribute to price convergence (Hulshof et al., 2016; Farag and Zaki, 2024). Additionally, the relatively shorter transportation distances between these markets result in lower transportation costs, further supporting price alignment.

For the empirical analysis, this study utilizes settlement prices of day-ahead contracts from four gas hubs: TTF, NBP, THE, and ZTP. Data for TTF, NBP, and THE are sourced from Refinitiv Datastream, while data for ZTP are obtained from the European Energy Exchange AG (EEX). The NBP gas price, originally denominated in GBP/therm, is converted to EUR/MWh to enable direct comparison with the other gas prices, which are measured in EUR/MWh.[7] The data cover the period from June 2019 to April 2024. Descriptive statistics for the natural gas price data are provided in Table A.1 in the Appendix. To ensure stationarity, this study uses price returns instead of raw prices for empirical estimations. Daily returns (r_t) are calculated using the standard log-difference formula: $r_t = (\ln p_t - \ln p_{t-1}) \times 100$, where p_t is the price at time t and ln denotes the natural logarithm. Using price returns captures price fluctuations and growth.

[7] To convert the NBP price to EUR/MWh, the spot exchange rate (GBP/EUR) and a conversion factor of 29.3071, reflecting the relationship between therms and MWh, are used.

Figure 1(a) plots TTF gas prices over the investigated period, while Figures 1(b), (c), and (d) show the price ratios between TTF and three other benchmarks. In 2020, TTF prices were relatively low, largely due to reduced economic activity and lower demand resulting from the COVID-19 lockdowns, mild winter temperatures in 2019–2020, and increased wind power generation in Europe (IEA, 2020). The figure also illustrates an unprecedented rally in prices beginning in March 2021, driven by several converging factors, including the post-pandemic economic recovery, a cold winter in Asia in early 2021, and a sharp decline in European domestic gas production, particularly from the Dutch Groningen field. Consequently, traders withdrew natural gas from storage to meet late winter demand, delaying reinjections (Heather, 2022). From September 2021, Russia reduced daily gas flows to Europe, fulfilling only long-term contracts while halting additional supplies to the spot markets, and underground storage levels remained low (Fulwood et al., 2022; Farag et al., 2023). In 2022, Russia further curtailed gas supplies following its invasion of Ukraine, exacerbating market stress. At the same time, the LNG market tightened due to both planned and unplanned outages, such as the prolonged outage at the Freeport LNG terminal in Texas, U.S., as well as unprecedented increases in charter rates, with global LNG infrastructure operating at maximum capacity (IEA, 2023). In 2023 and 2024, European gas price patterns stabilized after the extreme volatility of previous years, primarily driven by the rapid diversification of supply sources away from Russia through increased LNG imports and reductions in natural gas demand (ACER, 2023a; Ruhnau et al., 2023).

Figure 1(b) shows the ratio between THE and TTF. This ratio remained around 1, except during short periods in 2020 and the second half of 2022. Figures 1(c) and 1(d) depict the ratios of NBP to TTF and ZTP to TTF, respectively. These ratios also stayed close to 1, except in 2022 when they dropped to 0.5 or lower. The lower prices in Belgium and the UK during this period can be attributed to larger regasification capacities and the near-full utilization of cross-border pipeline infrastructure connecting these countries with the Netherlands and Germany.

This study uses absolute returns as a proxy for volatility. Defined as the absolute value of daily returns ($|r_t|$), they capture the magnitude of price fluctuations regardless of direction, thereby directly reflecting the intensity of market movements. Previous research has shown that absolute returns exhibit greater persistence than squared returns (Taylor, 2008; Ding et al., 1993). Additionally, Forsberg and Ghysels (2007) demonstrated that volatility measures based on absolute returns are less prone to sampling errors and more robust to jumps in asset prices. This proxy has also been employed in other studies on volatility connectedness (e.g., Huszár et al., 2023; Khalfaoui et al., 2023; Jaeck and Lautier, 2016). For robustness, we re-run our analysis using realized weekly volatility, estimated with the range volatility approach proposed by Parkinson (1980), in Section C.3 of the Appendix. The conclusions remain consistent with those obtained using absolute returns as a proxy.

Figure 2 illustrates the volatility dynamics of European gas markets from May 2019 to May 2024. The TTF volatility series (panel a) shows sharp spikes in 2022, particularly during the first few months and again

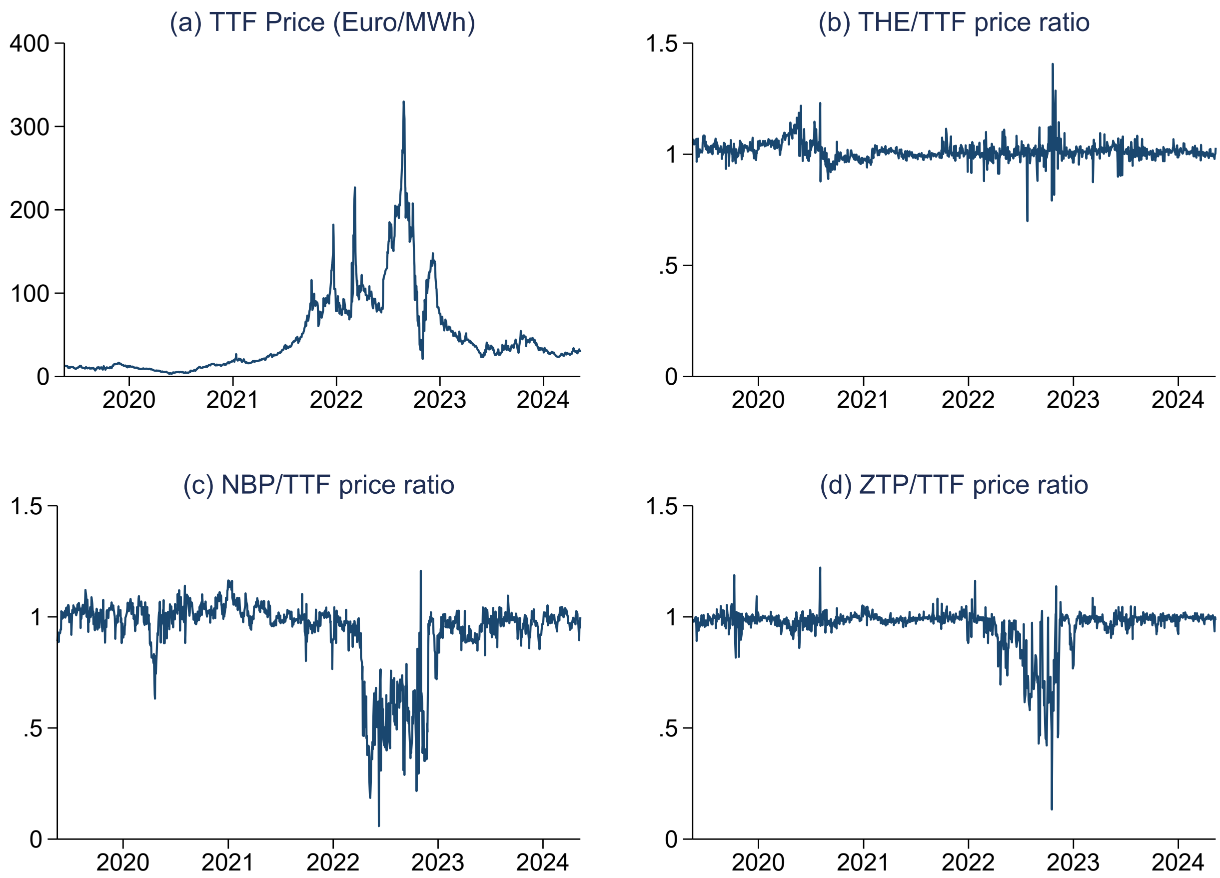

Figure 1: TTF price series and price ratios of THE, NBP, and ZTP to TTF
Note: The top left graph (a) shows the TTF price series (in Euro/MWh). The subsequent graphs display the price ratios: (b) THE/TTF, (c) NBP/TTF, and (d) ZTP/TTF, illustrating the relative price movements of the European gas benchmarks compared to TTF.

in August and September. These spikes coincide with heightened uncertainty about the future of Russian gas supplies and the evolving geopolitical situation in Ukraine, which increased market volatility during these periods. In 2023, TTF's volatility stabilized somewhat, though it remained slightly above the long-term average. By 2024, TTF experienced fewer dramatic price swings, indicative of further market rebalancing. The volatility ratios of THE/TTF, NBP/TTF, and ZTP/TTF (panels b, c, and d) demonstrate how the relative volatility of these markets compared to TTF evolved over time. For most of the period, these ratios remained moderate, indicating relatively aligned volatility between these benchmarks and TTF. However, in 2022, the NBP/TTF and ZTP/TTF ratios surged dramatically, signaling that these markets experienced disproportionately higher volatility than TTF during the peak of the crisis.

Two factors likely explain the higher volatility of NBP and ZTP compared to TTF. The first factor is the variation in market liquidity. TTF, Europe's most liquid gas hub, had a churn rate of 63 times in

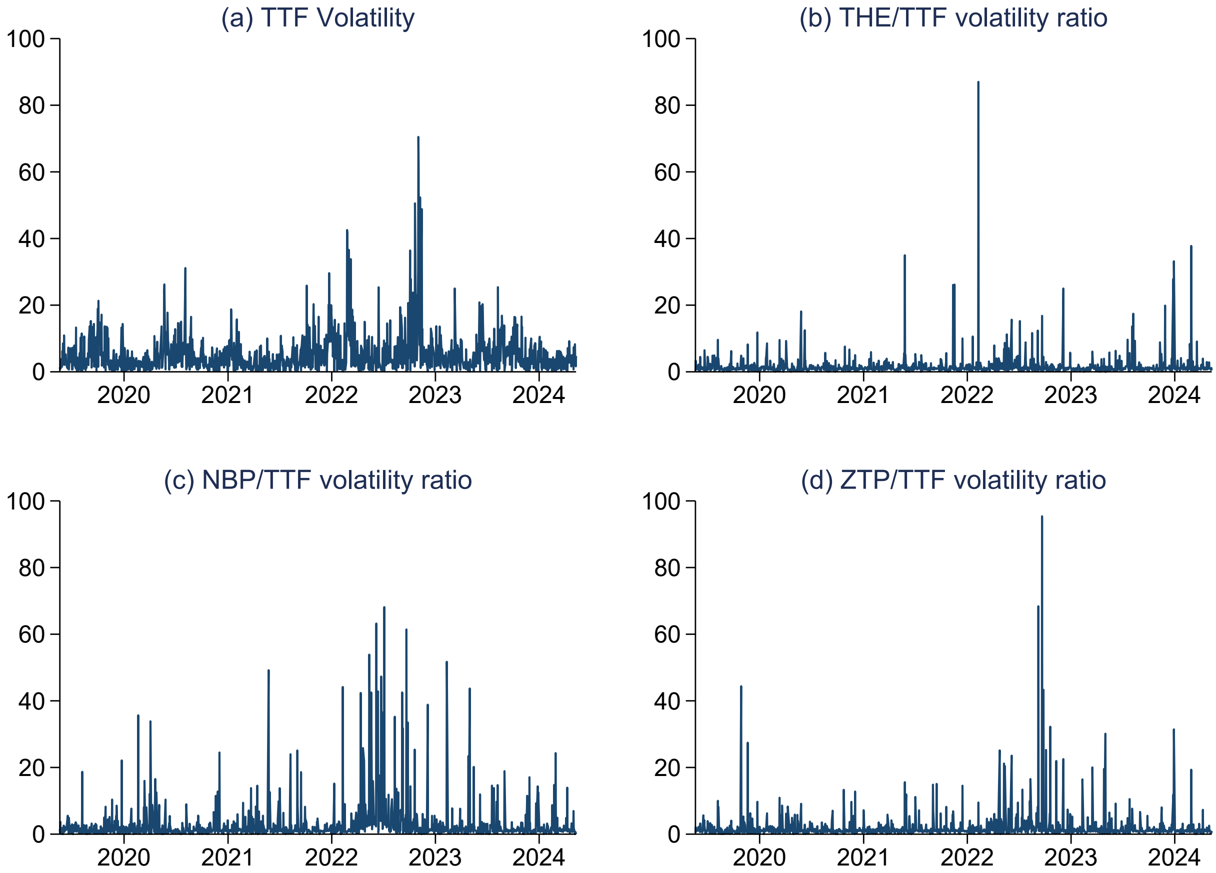

Figure 2: TTF volatility series and volatility ratios of THE, NBP, and ZTP to TTF
Note: The top left graph (a) shows the TTF volatility series, while the subsequent graphs display the volatility ratios: (b) THE/TTF, (c) NBP/TTF, and (d) ZTP/TTF, illustrating the relative volatility movements of the European gas benchmarks compared to TTF. Extreme observations for relative volatility were removed on June 10th, June 16th, and November 27th, 2022, to improve the visualization of graph (c).

2022, indicating high trading volumes and a large number of participants.[8] This high liquidity stabilizes prices, as large trades have less impact on the overall market. In contrast, NBP and ZTP had much lower liquidity, with NBP's churn rate dropping to 6.1 times, and ZTP categorized as a 'poor' hub with even lower liquidity. These lower liquidity levels made NBP and ZTP more vulnerable to price swings, as their markets were less able to absorb supply and demand shocks (Heather, 2024). The second factor is related to a substantial increase in LNG imports into both Belgium and the UK during 2022, with volumes rising by 175% year-on-year in Belgium and 70% in the UK. This surge in LNG supply inflated trading volumes relative to domestic demand in both countries, contributing to greater volatility (Heather, 2023).

[8]The churn rate is a measure of market liquidity, calculated as the ratio of the total volume of trades to the physical demand for gas within a market. A higher churn rate indicates more active trading relative to the volume of gas consumed, with a rate of 10 or more generally considered a benchmark of market maturity. Traders use the churn rate to assess a market's depth and liquidity, with financial participants often requiring a churn rate above 12 for engagement (IEA, 2020).

A key factor examined in relation to the varying levels of connectedness among the NWE gas hubs is the utilization of the physical infrastructure connecting these countries, particularly the interconnectors between the UK and the continent. Both gas interconnectors between the UK and continental Europe—namely, the UK–Netherlands (Figure 3(a)) and the UK–Belgium (Figure 3(b))—operated near full capacity for much of 2022, as shown in the figures. After Section 5 quantifies the level of connectedness, the subsequent section applies regression analysis to examine the relationship between congestion and the estimated connectedness levels.

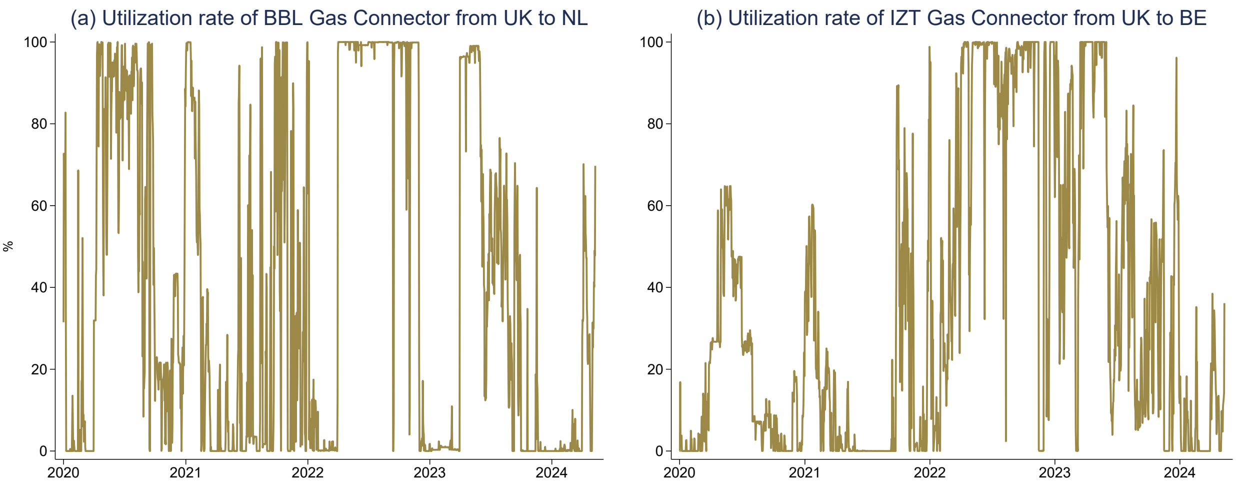

Figure 3: Gas infrastructure utilization in NWE
Note: Data obtained from the ENTSOG Transparency Platform. Country abbreviations: UK (United Kingdom), NL (Netherlands), BE (Belgium).

4. Methodology

This study applies a novel R^2 decomposed connectedness approach developed by Balli et al. (2023) to examine the overall, contemporaneous, and lagged spillover effects within European gas benchmarks. This approach extends the connectedness frameworks established by Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014) by integrating the generalized forecast error variance decomposition (GFEVD) with Genizi (1993)'s decomposition concept, allowing for a more accurate and computationally efficient estimation of connectedness measures, as it avoids the associated normalization problem. Specifically, the R^2 value of a multivariate regression model falls between 0 and 1, eliminating the need for scaling to constrain row sums within this range.[9] Consequently, this results in more easily interpretable connectedness measures, with the row sums automatically constrained to a functional range (Naeem et al., 2024a).

[9]The normalization problem arises when the row sums of the Generalized Forecast Error Variance Decomposition exceed 1, necessitating artificial scaling to bring them within the [0,1] range. The R^2 connectedness approach naturally constrains values within this range, eliminating the need for such normalization. See Naeem et al. (2024a) for a more detailed description of this issue and how the R^2 connectedness framework avoids it.

Consider the following VAR(p) with contemporaneous effects:

$$y_t = \sum_{i=0}^{p} A_i y_{t-i} + u_t, \quad u_t \sim N(0, \Sigma) \tag{1}$$

where y_t, y_{t-i}, and u_t are $N \times 1$ dimensional demeaned vectors in time t, A_i and Σ are $N \times N$ dimensional matrices. Here, $\text{diag}(A_0) = 0$, implying that the left-hand side (LHS) variable is dropped from the right-hand side (RHS) variables. In other words, the model ensures that each variable does not predict itself contemporaneously. p is the number of lags, with $p = 0$ meaning that the model collapses to the contemporaneous R^2 decomposed connectedness approach of Naeem et al. (2024a). Alternatively, the model presented can be expressed as: $y_{n,t} = a_n x_t + u_{n,t}$ where $x_t = \left[y_t, y_{t-1}, \ldots, y_{t-i}, \ldots, y_{t-p}\right]$ is an $N(p+1) \times 1$ dimensional vector and a_k is an $1 \times N(p+1)$ dimensional vector with zero on the nth position.

Only if all RHS variables are uncorrelated with each other does the sum of the R^2 contributions, determined through bivariate linear regressions, equal the R^2 goodness-of-fit measure of a multivariate linear regression (MLR). As this is generally not the case, there is a need to find a transformation that converts the correlated series $x_{n,t}$ into an orthogonal series. This can be achieved by using principal component analysis (PCA), where the count of latent factors is equal to the number of RHS variables. Hence, the decomposition of R^2 for an MLR can be calculated with:

$$R_{xx} = V\Lambda V^{'} = CC^{'} \tag{2}$$

$$C = V\Lambda^{1/2}V^{'} \tag{3}$$

$$R^{2,d} = C^2(C^{-1}R_{yx})^2 \tag{4}$$

Where V, $\Lambda = \text{diag}(\lambda_1,\ \lambda_2,\ \ldots,\ \lambda_{N(p+1)-1})$, and R_{xx} represent $[N(p+1)-1] \times [N(p+1)-1]$ eigenvector, eigenvalue, and Pearson correlation matrices, respectively. C is the $[N(p+1)-1] \times [N(p+1)-1]$ transformation matrix, which is used to derive R_{yx} and $R^{2,d}$, which are the $[N(p+1)-1] \times 1$ Pearson correlation and R^2 contribution vectors. R_{xx} denotes Pearson correlation coefficients across RHS variables, while R_{xy} is the Pearson correlation coefficient between the LHS and RHS variables. The first $N-1$ components of $R^{2,d}$ denote the contemporaneous R^2 contributions, and the remaining represent the lagged R^2 contributions. Hence, the vector sum of $R^{2,d}$ equals the MLR R^2 goodness-of-fit measure. Stacking the $R^{2,d}$ contribution of all N MLRs gives the $N \times N(p+1)$ dimensional $R^{2,d}$ decomposition matrix, $[R_0^{2,d},\ \ldots,\ R_i^{2,d},\ \ldots,\ R_p^{2,d}]$. $R_0^{2,d}$ can be interpreted as the contemporaneous spillovers ($R_C^{2,d}$), whereas the sum of the lagged values ($R_L^{2,d} = R_1^{2,d} + \ldots + R_i^{2,d} + \ldots + R_p^{2,d}$) stand for the lagged spillovers.

Based on Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014), $R_C^{2,d}$ and $R_L^{2,d}$ replace the scaled GFEVD matrix. Accordingly, the total connectedness index (TCI) is equal to the average R_n^2 of the N MLRs:

$$TCI = \frac{1}{N}\sum_{n=1}^{N} R_n^2 \tag{5}$$

Here, 'TCI' refers to the broader and more systematic relationships and interdependencies among multiple markets. It encompasses the overall structure and dynamics of how these entities are interconnected. Connectedness can be static or dynamic, reflecting how these relationships change over time, especially in response to economic or geopolitical events. As R_n^2 is within zero and unity, TCI is also within the same range, avoiding the connectedness normalization problem, which arises from the need to standardize the GFEVD to ensure that the row sums of the connectedness matrix are equal to one (Naeem et al., 2024a). The contemporaneous and lagged TCI is derived as follows:

$$TCI = \frac{1}{N}\sum_{n=1}^{N} R_n^2 \tag{6}$$

$$= \left(\frac{1}{N}\sum_{n=1}^{N}\sum_{j=1}^{N} R_{C,n,j}^{2,d}\right) + \left(\frac{1}{N}\sum_{n=1}^{N}\sum_{j=1}^{N} R_{L,n,j}^{2,d}\right) \tag{7}$$

$$= TCI^C + TCI^L \tag{8}$$

where TCI^C and TCI^L represent the contemporaneous and lagged TCI, respectively.

Furthermore, the 'TO', 'FROM', and 'NET' spillovers are calculated as follows:

$$TO_j = \sum_{n=1}^{N} R_{C,n,j}^{2,d} + \sum_{n=1}^{N} R_{L,n,j}^{2,d} \tag{9}$$

$$= TO_j^C + TO_j^L \tag{10}$$

$$FROM_j = \sum_{n=1}^{N} R_{C,j,n}^{2,d} + \sum_{n=1}^{N} R_{L,j,n}^{2,d} \tag{11}$$

$$= FROM_j^C + FROM_j^L \tag{12}$$

$$NET_j^C = TO_j^C - FROM_j^C \tag{13}$$

$$NET_j^L = TO_j^L - FROM_j^L \tag{14}$$

$$NET_j = NET_j^C + NET_j^L \tag{15}$$

In this context, the $\mathrm{TO}_j \left(\mathrm{TO}_j^C/\mathrm{TO}_j^L\right)$ total directional connectedness quantifies the proportion of the overall (contemporaneous/lagged) variance in all LHS variables that is attributable to series j. On the other hand, the $\mathrm{FROM}_j \left(\mathrm{FROM}_j^C/\mathrm{FROM}_j^L\right)$ total directional connectedness measures the extent to which the combined RHS variables explain the overall (contemporaneous/lagged) variance in series j. This is analogous to the R^2 value in a multivariate linear regression involving n variables. When NET_j is positive (negative), series j acts as a net transmitter (receiver) of shocks, meaning it explains more (less) of the variation in other series than the others explain in it. This interpretation applies equally to both contemporaneous and lagged connectedness measures.

5. The connectedness of NWE gas markets

This results section presents the findings of our connectedness analysis in three parts. First, we analyze the connectedness of natural gas price returns, covering both overall and directional dynamics.[10] Second, we examine volatility connectedness, focusing on similar aspects. Finally, we extend our analysis to futures prices to explore how expectations and forward-looking information are shared among markets.

5.1. Return connectedness results

Figure 4 plots the overall connectedness index from 2020 to 2024 for the four gas benchmarks. This index measures the extent to which price movements in one hub are transmitted to others. The figure also shows the decomposition of this index into contemporaneous spillovers (blue line) and lagged spillovers (red line). The results indicate that connectedness in natural gas price returns was around 70% in 2020 and increased to approximately 80% in 2021. It dropped sharply in the second half of 2022, coinciding with market disruptions and supply issues following the Russia-Ukraine invasion and the consequent cuts in Russian gas supply. This finding aligns with the results of Szafranek et al. (2023) for the European gas market, as well as Balli et al. (2023) and Naeem et al. (2024a) for futures prices of various energy commodities. Our analysis of the extended sample up to 2024 reveals that connectedness began to rise rapidly in the second half of 2023, reaching the highest level observed by the end of the sample, a level previously seen in the second half of 2021. These findings show that the dynamic total connectedness index fluctuates over time and is dependent on market events. This observation is consistent with Broadstock et al. (2020) and Papież et al. (2022), who also find that various market reforms and external economic and political events influence market connectedness. A summary of the averaged connectedness measures among the four return series throughout the sample period is provided in Table A.2 in the Appendix.

Furthermore, Figure 4 illustrates that contemporaneous interdependencies, shown in blue, are more prominent than lagged interdependencies, depicted in red. This indicates that most of the variation in connectedness is driven by immediate reactions rather than past interactions. The stronger contemporaneous dependency underscores the dominance of immediate market reactions over delayed responses, suggesting that market participants react swiftly to new information, with price adjustments among the gas hubs occurring almost instantly. This result aligns with the findings of Balli et al. (2023), who also observed the dominance of contemporaneous effects in the connectedness between energy futures prices. We argue that this pattern holds for natural gas price hubs before, during, and after the crisis, reflecting the rapid dissemination of the effects of shocks driven by news and events across hubs.

[10] Our baseline analysis uses a 200-day rolling-window VAR model with Pearson correlation coefficients. Robustness checks using varying window sizes (150 and 250 days) and Spearman correlations show consistent results, confirming the stability and validity of the findings. For brevity, these results are provided in Appendix Section C.

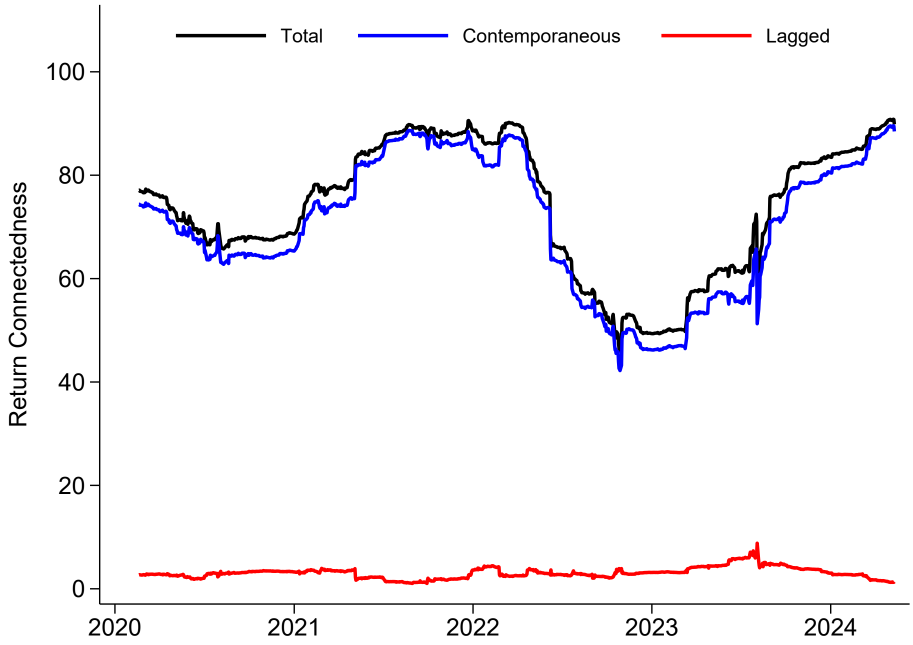

Figure 4: Dynamic total connectedness of return series

Notes: R^2 decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one (BIC).

The dominance of contemporaneous effects in the overall connectedness of the NWE gas market, even during periods of infrastructure congestion, can be attributed to the advanced trading mechanisms and financial instruments used in these markets. Specifically, market participants employ virtual trades and locational swaps,[11] as well as derivatives, to adjust their positions quickly in response to new information. These tools enable the rapid dissemination of price signals across hubs, ensuring that prices adjust promptly, even when physical gas flows are restricted. Additionally, the need to secure transmission capacity or hedge against price differences between hubs further incentivizes swift action by market participants. As a result, price adjustments reflect new information immediately, across varying market conditions (ACER, 2023b).

Thus far, we have discussed the overall connectedness level, which is of interest but disregards heterogeneity within the connectedness of the gas price hubs as well as directional information. We now turn to hub-specific directional connectedness measures. The results are depicted in Figure 5, which includes three rows: the 'FROM' connectedness (first row), measuring how much a particular hub's price movements are explained by shocks from other hubs; the 'TO' connectedness (second row), reflecting how much a hub contributes to price variations in other hubs; and the 'NET' connectedness (third row), indicating whether a hub is a net transmitter or net receiver of shocks within the system. Additionally, the figure presents the respective overall

[11] A locational swap refers to a virtual transaction where a trader exchanges gas between two markets without physically moving the gas. The trader sells gas in one market and simultaneously buys gas in another, profiting from the price difference between the two hubs. This eliminates the need for a physical transportation contract and is considered 'virtual transport' (see ACER (2023b) for more details).

R^2 measure of connectedness, along with the contemporaneous and lagged decomposed measures. The results indicate that the 'FROM' and 'TO' connectedness indices for the four gas benchmarks generally decreased in the second half of 2020, following the initial impact of the COVID-19 pandemic, and again from the second quarter of 2022 to the first quarter of 2023. However, ZTP's indices were lower during these subperiods of decreased connectedness, and NBP's indices dropped even more significantly. This suggests that during times of severe market disruptions, ZTP and NBP became less influential in transmitting and receiving price shocks from other hubs. These results indicate that local factors and individual market conditions began to dominate price movements rather than shared regional dynamics during tight market conditions. Furthermore, the decomposition of these 'FROM' and 'TO' connectedness indices reflects the dominance of the contemporaneous effects. This implies that even when NBP and ZTP became less connected overall during periods of market stress, the limited spillovers that persisted were transmitted instantaneously.

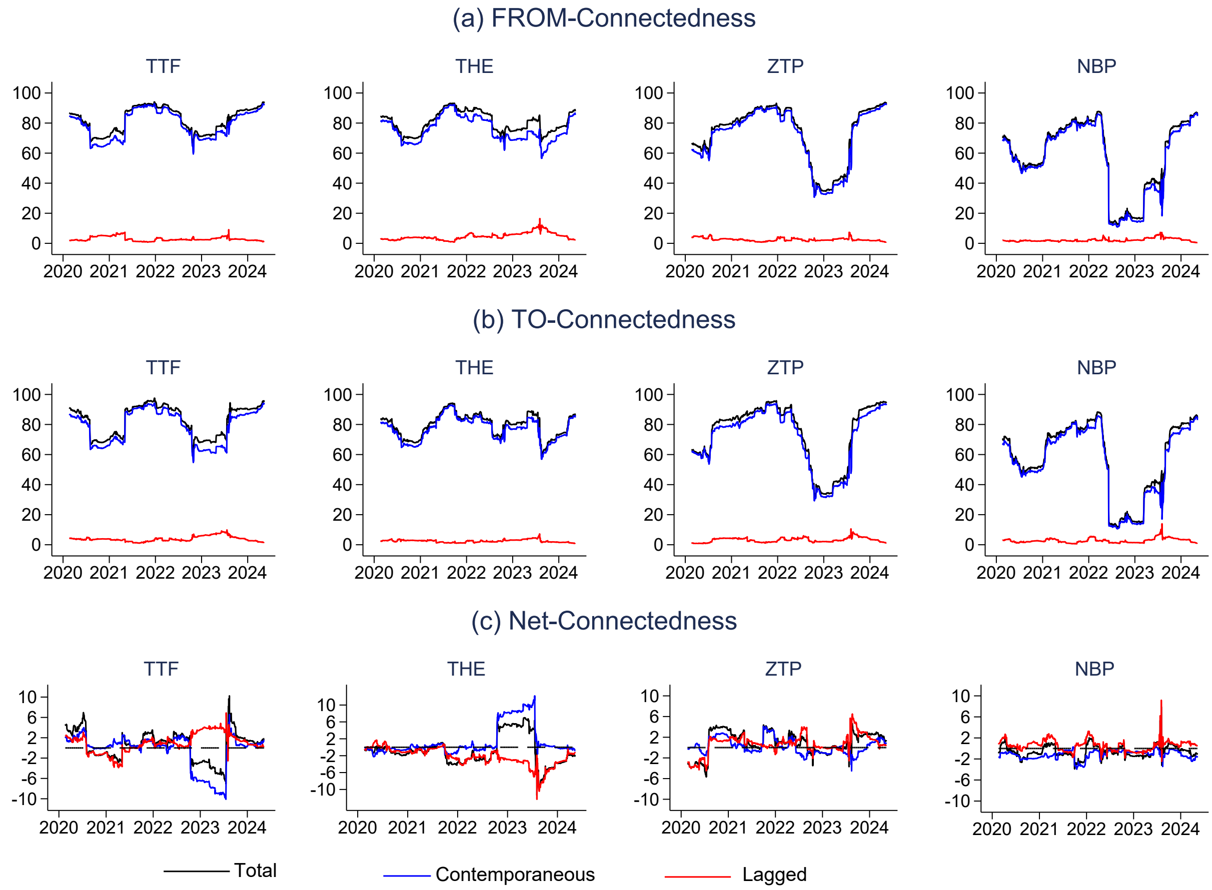

Figure 5: Dynamic directional connectedness of return series

Notes: R^2 decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one. The black line visualizes the overall dynamic total connectedness, while the dynamic contemporaneous and lagged connectedness are illustrated in blue and red, respectively. The dashed horizontal line in Figure (c) represents the zero value reference line

The third row of Figure 5 shows the time-varying net total directional connectedness of the four gas benchmarks. The results indicate that TTF usually acted as a net transmitter of shocks, except from late 2022 to late 2023, when it became a net receiver, and THE became a net transmitter. A potential explanation for this shift is Germany's urgent need to replace lost Russian pipeline gas, which led to increased spot trading at THE. Additionally, the construction of new LNG import facilities and Floating Storage Regasification Units (FSRUs) in Germany further solidified THE's role as a key hub for balancing the country's gas needs and managing supply risks during this period of heightened energy insecurity. This argument is supported by the high market activity score reported by Heather (2023) for THE in 2022, which was second only to the Dutch TTF.[12] ZTP exhibited a more varied pattern: initially, it was a net receiver until the first half of 2020, then predominantly a net transmitter, before reverting to a net receiver during the same period as TTF. Lastly, NBP remained a net receiver for most of the analyzed period. The results also reveal that NBP's directional connectedness is primarily driven by contemporaneous effects, indicating that it quickly absorbs and reflects shocks originating from other hubs. For TTF, contemporaneous net spillover effects closely align with the overall net spillover effects throughout the entire sample period, reflecting that its influence on other hubs is immediate. This could be attributed to the high liquidity and significant trading activity of TTF.[13] This aligns with Liu et al. (2024), who found that markets with a substantial trader base have their net connectedness highly influenced by contemporaneous effects. For THE and ZTP, this higher similarity between contemporaneous net spillover effects and overall net spillover effects only occurs during periods of positive net connectedness.

5.2. Volatility connectedness results

Next, we examine the dynamic joint total connectedness of the volatility series, as shown in Figure 6. High volatility connectedness indicates that periods of heightened uncertainty or volatility in one market can influence risk perceptions and price fluctuations in other markets, often through the transmission of market stress or shocks. The results show that the volatility connectedness of these benchmarks ranges between 40% and 70%. While this is somewhat lower than the return connectedness analyzed earlier, the connectedness of both time series follows a similar trajectory. The spillover effects reached a high level from the second half of 2021 to the first quarter of 2022, suggesting that interconnectedness among volatility series was high during this period. The peak in the first quarter of 2022, particularly in February 2022, coincides with the Russian invasion of Ukraine. This can be attributed to increased investor caution caused by economic uncertainty

[12] This score reflects the overall level of market activity at a hub, including the number of active participants, traded products, total traded volumes, the tradability index, and the churn rate. A higher score indicates greater liquidity, a wider diversity of traded products, and a hub's ability to facilitate risk management and portfolio balancing (see Heather (2023) for more details).

[13] Note that TTF is by far the most liquid hub in the European gas market and has been widely used as the reference price for physical wholesale gas contracts. For a detailed analysis of the liquidity of different European gas benchmarks, refer to Heather (2023).

and the market reconfiguration following this major news shock (Naeem et al., 2024b). Following this, the dynamic TCI values for the volatility series gradually declined, reaching the lowest level in early October 2022 at 40%. This decline was potentially due to the aftermath of subsequent shocks, such as the demolition of the Nord Stream 1 and 2 pipelines and the disruption of Russian gas flow to Europe. The results also indicate that throughout the observation period, contemporaneous effects dominated volatility connectedness (approximately 95%), except in the first half of 2023, when lagged effects increased slightly. These findings suggest that news affecting one market can lead to an immediate reassessment of risks in other markets, resulting in contemporaneous volatility spillovers. The slight increase in lagged effects in the first half of 2023 suggests that as markets adjusted to the post-crisis environment, the transmission of volatility may have become slightly more gradual.

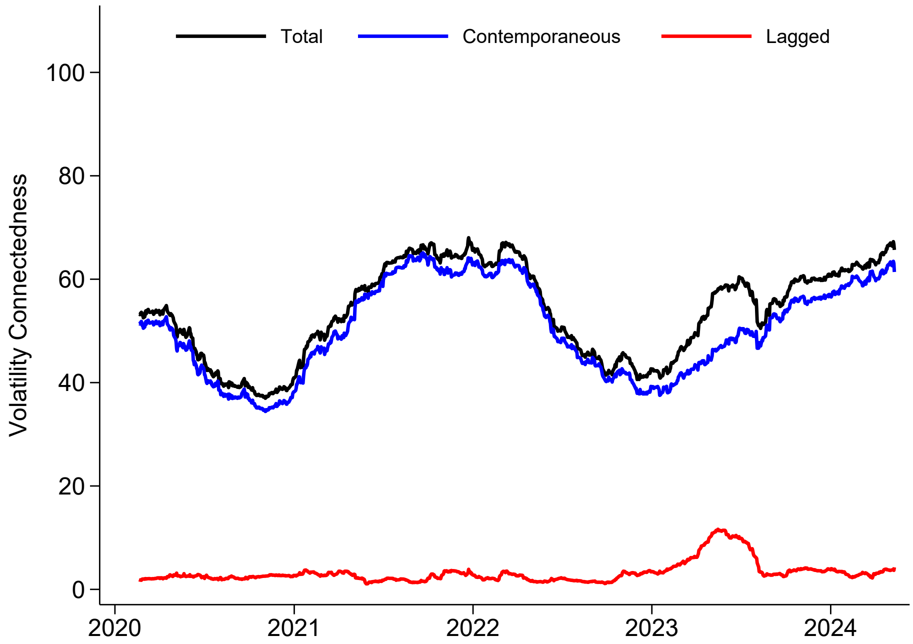

Figure 6: Dynamic total connectedness of volatility series

Notes: R^2 decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one (BIC). Volatility is measured by the absolute returns and included in the model in log transformation.

Figure 7 presents the dynamic directional connectedness results of the volatility series, including 'FROM,' 'TO,' and 'NET' connectedness. Similar to the results obtained for return connectedness, the FROM' and 'TO' volatility connectedness indices for the four gas benchmarks generally decreased in the latter half of 2020 after the initial impact of COVID-19, and again from Q2 2022 to Q1 2023. ZTP and NBP experienced more pronounced declines in their indices during these periods of market stress, with ZTP showing lower values and NBP experiencing even sharper drops, approaching zero. This indicates that ZTP and NBP were less influenced by the other benchmarks during severe disruptions.

The third row of Figure 7 reveals distinct patterns among the gas benchmarks over the observed periods. The TTF benchmark oscillates between being a net transmitter and a net receiver of volatility, highlighting its pivotal role in the NWE gas market, where its influence fluctuates in response to market conditions and external factors. For example, TTF was a net transmitter during the first half of 2020 and throughout 2022, aligning with periods of high market activity or stress, such as the onset of the COVID-19 pandemic and the geopolitical tensions impacting energy supplies. THE was predominantly a net receiver, except from the second half of 2021 to the end of the first half of 2022. The specific role of THE as a net transmitter in the second half of 2022 is likely due to Germany's policy actions regarding the mandate of storage filling. ZTP consistently acted as a net receiver, except during the period from 2020 to the first half of 2021, and again in the first half of 2023, when it became a net transmitter. The strong influence of ZTP on other benchmarks may be surprising given its relatively low liquidity, but this could be explained by its central geographic location between the other investigated markets. Conversely, NBP was largely a net receiver, highlighting its reactive nature, with brief periods as a net transmitter at the end of 2021 and in the first half of 2023, suggesting short-term market anomalies. These findings indicate that TTF and ZTP play significant roles in market integration and stability, while THE and NBP are more susceptible to external shocks. Moreover, the decomposition of TTF's net connectedness into contemporaneous and lagged effects reveals that contemporaneous effects dominated the directional connectedness for most of the time in the investigated sample. In contrast, for the other three hubs, net directional connectedness was mainly driven by lagged effects. This reflects the role of market liquidity; the other three hubs have lower liquidity compared to TTF, causing their influence on other markets to take more time to materialize. Additionally, local factors such as domestic policies and storage levels contribute to a more gradual transmission of shocks.

For robustness, we also use the range-based volatility measure of Parkinson (1980) to reanalyze the connectedness in the European gas market. The detailed results of this analysis are presented in Section C of the Appendix. The findings are consistent with those of the baseline analysis.

5.3. Connectedness analysis using futures prices

This section investigates gas market connectedness based on futures prices, specifically one-month-ahead prices, rather than the spot prices (day-ahead prices) used in the previous subsections. The intuition behind this analysis is that futures prices incorporate traders' anticipations of upcoming supply and demand shifts, geopolitical risks, and macroeconomic factors. A high level of connectedness indicates that market participants across different hubs share similar expectations about the future, leading to synchronized futures price movements. Therefore, we hypothesize that futures prices may exhibit different connectedness patterns compared to spot prices, which are influenced by immediate physical constraints and short-term market dynamics, such as local supply disruptions, weather conditions, and pipeline capacities.

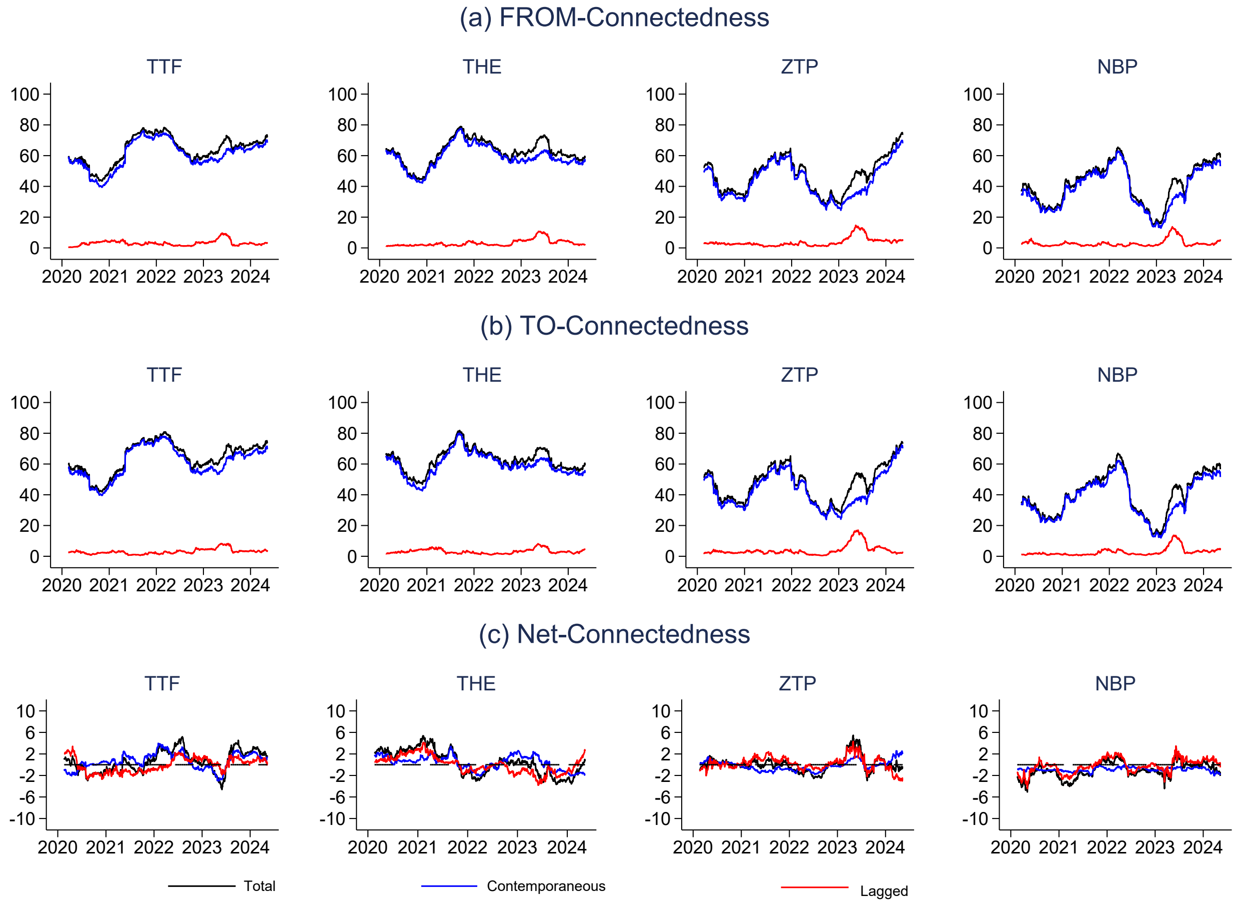

Figure 7: Dynamic directional connectedness of volatility series

Notes: R^2 decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one. The black line visualizes the overall dynamic total connectedness, while the dynamic contemporaneous and lagged connectedness are illustrated in blue and red, respectively.

In the following, we focus on the total return connectedness, which is presented in Figure 8. Additional results are provided in the Appendix, where Figure A5 displays the directional connectedness of return series, Figure A6 presents the total volatility connectedness, and Figure A7 illustrates the directional connectedness of volatility series. For all figures, spot and futures price results are presented together for easy comparison. The dynamic decomposition of overall connectedness with futures prices leads to similar conclusions as with spot prices, with the contemporaneous effect being the dominant factor.[14]

Figure 8 indicates that during the initial phase of the COVID-19 pandemic (2020 to early 2021), futures prices exhibited higher connectedness than spot prices. This suggests that market participants shared similar expectations about future market conditions, leading to synchronized futures price movements. As the pandemic's impact eased in the second half of 2021, connectedness among spot prices surpassed that of futures prices, reflecting a resurgence in physical market interdependence and aligned supply-demand dynamics across

[14]These results are omitted from the figures for brevity but are available upon request from the corresponding author.

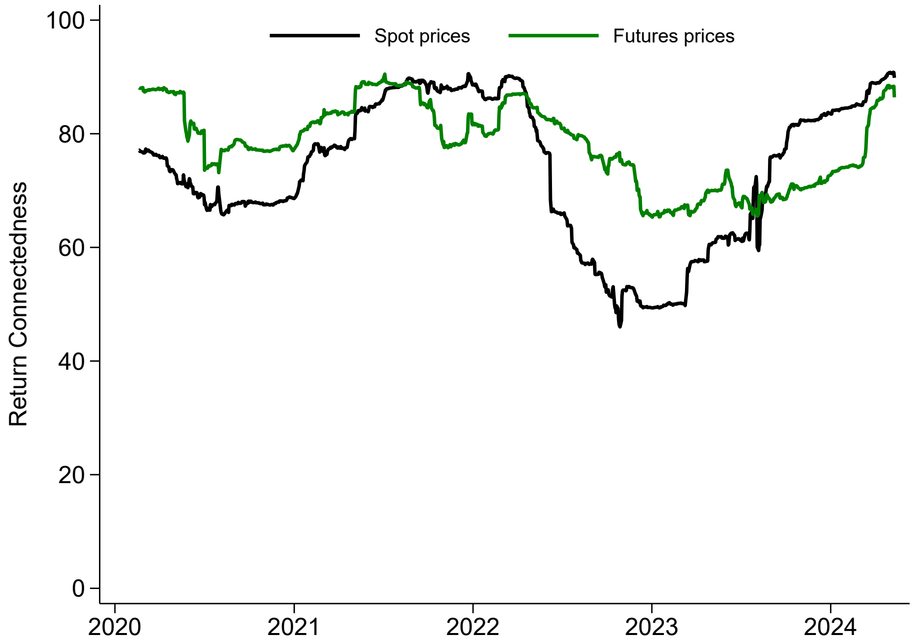

Figure 8: Comparison of return connectedness indices: spot prices vs. futures prices
Notes: R^2 decomposed measures are based on a 200-day rolling-window rolling-window VAR model.

hubs. From February 2022 until mid-2023, geopolitical tensions stemming from the Russia-Ukraine conflict and associated supply disruptions led to a less pronounced decline in connectedness among futures prices. This suggests that market participants collectively anticipated tighter future markets due to reduced Russian gas supplies and infrastructure constraints, resulting in synchronized futures price movements. Concurrently, physical limitations and localized supply issues caused spot prices to diverge, reducing their connectedness. In the latter half of 2023 and early 2024, as markets stabilized and infrastructure constraints eased, spot prices became more interconnected. The normalization of physical flows allowed spot prices to move more cohesively across hubs, while futures price connectedness slightly diminished as market expectations varied in a less uncertain environment.

Overall, these findings highlight the interplay between physical market conditions and market expectations in shaping the interconnectedness of gas prices. Periods of heightened uncertainty and shared future concerns tend to amplify futures price connectedness, whereas improved physical integration and immediate market alignment enhance spot price connectedness.

6. Factors associated with the connectedness of NWE gas markets

The connectedness analysis from the previous section reveals notable fluctuations in connectedness levels. The lowest level occurred at the end of 2022, coinciding with a tight supply situation in Germany and the Netherlands, as these countries had to replace Russian supplies with LNG and increased pipeline supplies from Norway and the UK. Our directional connectedness analysis shows that the decrease in connectedness was mainly due to the decoupling of the NBP benchmark, likely caused by physical congestion at cross-border pipelines. This congestion may have limited the ability to balance gas supply and demand across the regional markets, thereby reducing interdependence and price coherence.

This section examines the relationship between congestion in the pipelines connecting the UK with the other investigated markets and the connectedness of the NWE gas markets. Figures 9(a) and 9(b) depict the utilization rates of the BBL gas connector from the UK to the Netherlands and the IZT gas connector from the UK to Belgium, respectively. These figures visually support the hypothesis that periods of high utilization in either of the two pipelines correlate with lower connectedness levels, while periods of low utilization are associated with increased connectedness.

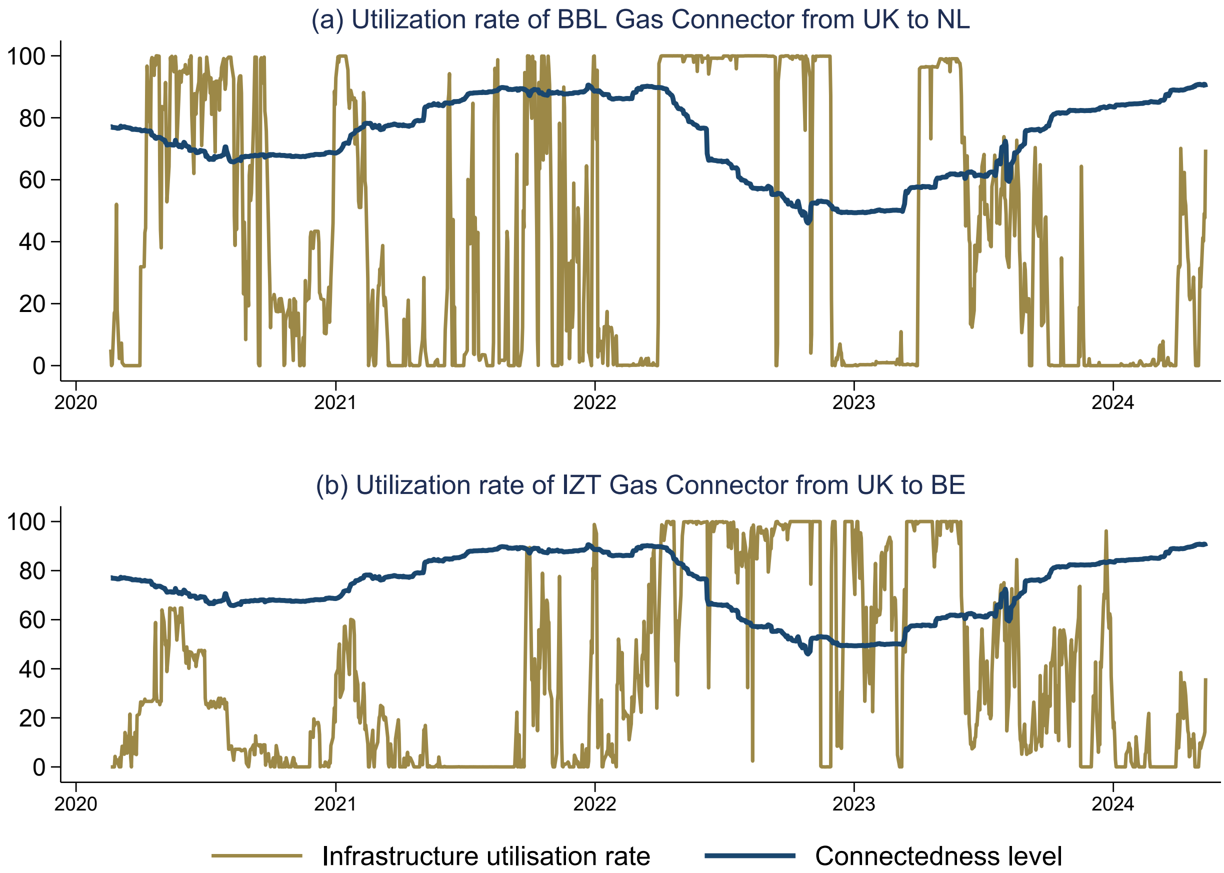

Figure 9: Return connectedness level and utilization rate of BBL and IZT gas pipelines (%)
Notes: Data on utilization rates are obtained from the ENTSOG Transparency Platform. The solid line represents return connectedness between the NWE gas benchmarks, as analyzed in Subsection 5.1. Values on the vertical axis are expressed as percentages (%). BBL refers to the Balgzand-Bacton Line pipeline, and IZT refers to the Interconnector Zeebrugge Terminal pipeline. Country abbreviations: UK (United Kingdom), NL (Netherlands), and BE (Belgium).

To further investigate the effect of pipeline congestion, along with other factors, on connectedness levels, we conduct a regression analysis to quantify how congestion in the BBL and IZT gas pipelines correlates with the connectedness of the NWE natural gas benchmarks. The dependent variables are total return and volatility connectedness, as obtained from the analysis in the previous section. The main independent variable is 'congestion,' a dummy variable that takes the value of 1 if the BBL or IZT pipeline is congested, defined as having a utilization rate of 80% or higher.

We include a control variable to account for the impact of the EU's 2022 storage mandate, which required member states to fill their gas storage facilities to 80% capacity by November 1, 2022. This mandate was issued by the EU Council on June 27, 2022 (Council of the European Union, 2022). The hypothesis is that this storage mandate created immediate and intense pressure to secure gas supplies across the EU, particularly in Germany, during already tight market conditions, leading to higher prices in the eastern part of the NWE region. To measure this effect, we created a dummy variable that takes the value of 1 starting on June 27, 2022, when the mandate was issued, and ending on August 29, 2022, when the storage target of 80% was reached (Gas Infrastructure Europe, 2022).

We also control for geopolitical risk by including the Geopolitical Risk Index from Caldara and Iacoviello (2022) to isolate and better understand how external political factors influence market integration.[15] Additionally, we include the futures spreads of TTF and NBP as well as interaction terms between the futures spreads and the IZT congestion dummy variable.[16] The futures spread is calculated as the difference between future and spot prices and, therefore, closely related to the level of gas inventories and the net convenience yield (Valenti, 2022). When the futures spread is positive, it indicates that futures prices are higher than spot prices, suggesting that traders expect gas prices to rise. This can lead to increased gas storage, as market participants prefer to hold onto their inventory in anticipation of higher future prices, impacting overall market dynamics. Therefore, interacting the futures spread with congestion captures the combined effect of infrastructure constraints and market expectations on gas market connectedness, helping us understand how pipeline congestion is influenced by traders' expectations of future gas prices. Lastly, we control for year- and month-fixed effects in all regressions to account for time-specific factors and seasonal variations that could influence gas market connectedness.

The results are presented in Table 1, which displays the regression analysis for return connectedness (columns 1–2) and volatility connectedness (columns 3–4). In each set of regressions, the first specification includes only the BBL and IZT variables to capture the effect of pipeline utilization on the connectedness indices. The second specification introduces additional independent variables.

The results indicate that the coefficient for the IZT variable is negative and statistically significant across all specifications, indicating a strong association between IZT pipeline congestion and decreased return

[15]The index measures adverse geopolitical events based on articles from 10 U.S. newspapers. More details about the index and data can be found on this website: https://www.matteoiacoviello.com/gpr.htm.

[16]We focus on the TTF and NBP benchmarks because they are the most liquid in the region and focus on IZT congestion because this was found to be more significant (see Table 1).

Table 1: Regression analysis of factors associated with NWE gas markets connectedness

	(1)	(2)	(3)	(4)
	Return connectedness		Volatility connectedness	
BBL	-3.016	-0.631	-1.764	-0.681
	(2.598)	(1.385)	(1.660)	(1.477)
IZT	-12.817^{a}	-9.587^{a}	-7.123^{a}	-4.711^{b}
	(3.385)	(3.363)	(2.152)	(1.975)
Geopolitical Risk		0.049^{a}		0.031^{a}
		(0.017)		(0.010)
EU Storage Mandate		-7.471^{c}		-5.647^{b}
		(4.447)		(2.694)
Spread_{ttf}		0.160		0.089
		(0.161)		(0.118)
Spread_{nbp}		-0.307^{b}		-0.113
		(0.143)		(0.084)
IZT $\times$ Spread_{ttf}		-0.454^{b}		-0.205
		(0.179)		(0.129)
IZT $\times$ Spread_{nbp}		0.217^{b}		0.052
		(0.105)		(0.075)
Intercept	65.909^{a}	59.681^{a}	39.169^{a}	35.706^{a}
	(4.408)	(4.066)	(4.302)	(3.919)
No. of observations	1103	1103	1103	1103
Adj. R^2	0.514	0.625	0.518	0.578
Year FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓

Notes: The dependent variable for columns 1–2 is the return connectedness index, while the dependent variable for columns 3–4 is the volatility connectedness index. The variables "BBL" and "IZT" relate to the "Congestion" of the respective pipeline, which is measured by a dummy set to 1 if the respective pipeline's utilization rate exceeds 80%. "EU Storage Mandate" is a dummy variable that takes the value of 1 from June 27, 2022, to August 29, 2022. "Spread" is the futures spread (futures - spot) for the TTF and NBP gas benchmarks. Standard errors are reported in parentheses and are computed using the Newey-West heteroskedasticity and autocorrelation consistent estimator. All regressions control for year and month-fixed effects, and their results are available upon request from the corresponding author. ^{a}, ^{b}, and ^{c} represent the 1%, 5%, and 10% significance levels, respectively.

connectedness in the NWE gas markets. For example, column (1) shows that IZT congestion is associated with a decrease of 12.817 units in the connectedness index. When control variables are added in the second regression, the effect decreases (in absolute terms) to -9.587 units but remains statistically significant at the 1% level. This suggests that IZT congestion substantially correlates with market connectedness, even after accounting for geopolitical risk, the EU storage mandate, and futures spreads. The BBL variable, however, is not statistically significant in any of the regressions for return connectedness, indicating no significant association between BBL pipeline congestion and return connectedness beyond the extent to which BBL and IZT congestion correlated.[17] This may be due to the IZT pipeline's more critical role in connecting the NWE gas markets or possible differences in the capacity or usage patterns of the two pipelines.[18]

The results also show that geopolitical risk has a positive coefficient statistically significant at 1%, suggesting that higher geopolitical risk is correlated with increased market connectedness. This implies that geopolitical events may cause markets to move more in parallel due to shared concerns, thereby increasing connectedness. Regarding the EU storage mandate, the results indicate that this policy may have had a negative effect on connectedness.[19] Column 2 also indicates that the interaction between IZT and the TTF futures spread is negative (-0.454) and statistically significant at the 5% level, suggesting that during congestion, expectations of higher future prices (a positive TTF spread) further reduce current connectedness. This may be due to anticipated supply shortages exacerbating market segmentation. Conversely, the interaction between IZT and the NBP futures spread is positive (0.217) and also significant at the 5% level, indicating that the negative impact of the NBP spread on connectedness is moderated during congestion. However, we do not find a statistically significant effect for these two interaction terms on volatility connectedness.

7. Conclusion

This study examines the time-varying connectedness among natural gas prices in the NWE market using the R^2 decomposed connectedness approach, as introduced by Balli et al. (2023). This method decomposes connectedness measures into contemporaneous and lagged components, providing a more nuanced understanding of market dynamics. The analysis is applied to both price returns and volatility.

Our analysis reveals that connectedness within natural gas markets is highly dynamic and varies significantly depending on market conditions, such as external shocks and infrastructure congestion. The findings consistently show that contemporaneous effects dominate lagged effects in both return and volatility connectedness, indicating that immediate market responses are more influential than delayed reactions. This trend is particularly evident during periods of heightened uncertainty, such as the Russia-Ukraine crisis. Furthermore, futures and spot prices exhibit distinct connectedness patterns shaped by different underlying factors. Futures price connectedness tends to increase during periods of uncertainty, driven by shared market

[17] In fact, the Variance Inflation Factor (VIF) values for the BBL and IZT variables were below 5 in all regressions, indicating that multicollinearity is not a concern. The VIF results are available upon request.

[18] The IZT pipeline has a significantly higher capacity for transporting natural gas compared to the BBL pipeline. IZT provides an export capacity of 20 bcm/year (UK to BE) and an import capacity of 25.5 bcm/year (BE to UK), translating to approximately 637 GWh/day and 812 GWh/day, respectively. In contrast, BBL's forward flow (NL to UK) capacity is 432 GWh/day, while its reverse flow (UK to NL) capacity is only 185 GWh/day (Sources: https://www.fluxys.com/ and https://bblcompany.com/).

[19] We also estimate another specification that controls for the German Gas Storage Act, issued on April 30, 2022, which required storage operators in Germany to reach at least 80% capacity by October 1, 2022. Specifically, we tested a model that included a dummy variable for this German mandate and another with an interaction term between the EU and German mandates. However, the results for both the German mandate dummy and the interaction term were statistically insignificant. Meanwhile, the EU mandate dummy remained significant, producing results consistent with the baseline specification.

expectations of future conditions, whereas spot price connectedness is enhanced by improved physical integration and immediate market alignment. We also find that pipeline congestion is significantly associated with reduced market connectedness, underscoring the impact of infrastructure constraints on the integration of NWE gas markets. The interaction between congestion and market expectations further exacerbates the decline in connectedness, suggesting that infrastructure limitations, combined with expectations of future price increases, can intensify market segmentation. Conversely, heightened geopolitical risk is correlated with increased connectedness, indicating that shared regional responses to geopolitical events can enhance the alignment of market behaviors across hubs.

Our findings have three main implications. First, the dominance of contemporaneous spillovers in both return and volatility connectedness indicates that European gas markets respond quickly to shocks, even during tight market conditions. This suggests that, despite supply constraints or pipeline congestion, information flows and price adjustments are not hindered, driven by trading mechanisms that allow participants to bypass physical bottlenecks through financial instruments and virtual trades. As a result, relying on past shocks to predict future movements is less effective, and market participants need to focus on real-time information and be prepared to act swiftly. However, this also implies that participants have limited time to respond to shocks, potentially increasing their exposure to sudden market volatility. Consequently, constant monitoring and rapid decision-making become critical to mitigate heightened risks.

Second, the decrease in connectedness between European gas markets during crises and tight market conditions underscores the significant impact of physical infrastructure constraints. Unlike financial markets, where crises typically heighten return and volatility spillovers through contagion effects (see, for example, Longstaff, 2010; Mensi et al., 2018), our results indicate that congestion in gas pipelines during crisis periods can disrupt market integration, leading to reduced connectedness. This phenomenon is consistent with similar findings in other energy markets, such as the European electricity market (e.g., Gugler et al., 2018). However, once these tight conditions subside, connectedness swiftly returns to normal levels, suggesting that these disruptions are temporary and that the market can restore integration once physical constraints ease.

Lastly, the relationship between pipeline utilization and market connectedness has direct welfare implications. During periods of pipeline congestion, reduced connectedness limits arbitrage opportunities, leading to higher price dispersion across regions and potentially lowering welfare due to inefficient gas allocation. While this generally supports infrastructure enhancements, further expansion of the European natural gas infrastructure should be carefully considered. As we show, connectedness levels had already returned to pre-crisis levels toward the end of our observation period. Further infrastructure investments may, hence, risk becoming stranded assets.

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References

ACER, 2023a. Addressing congestion in north-west european gas markets. URL: https://acer.europa.eu/sites/default/files/documents/Publications/ACER_Special_Report_Congestion2023.pdf. accessed: 2024-06-12.

ACER, 2023b. European gas market trends and price drivers - 2023 market monitoring report. URL: https://www.acer.europa.eu/sites/default/files/documents/Publications/ACER_MMR_2023_Gas_market_trends_price_drivers.pdf. accessed: 2024-09-22.

Alexander, C., Wyeth, J., 1994. Cointegration and market integration: An application to the indonesian rice market. The Journal of Development Studies 30, 303–334.

Alizadeh, S., Brandt, M.W., Diebold, F.X., 2002. Range-based estimation of stochastic volatility models. The Journal of Finance 57, 1047–1091.

Anderson, S.P., Ginsburgh, V.A., 1999. International pricing with costly consumer arbitrage. Review of International Economics 7, 126–139.

Anscombe, F.J., Glynn, W.J., 1983. Distribution of the kurtosis statistic b 2 for normal samples. Biometrika 70, 227–234.

Asche, F., Osmundsen, P., Tveterås, R., 2002. European market integration for gas? volume flexibility and political risk. Energy Economics 24, 249–265.

Balli, F., Balli, H.O., Dang, T.H.N., Gabauer, D., 2023. Contemporaneous and lagged r2 decomposed connectedness approach: New evidence from the energy futures market. Finance Research Letters 57, 104168.

Baruník, J., Křehlík, T., 2018. Measuring the frequency dynamics of financial connectedness and systemic risk. Journal of Financial Econometrics 16, 271–296.

Bastianin, A., Galeotti, M., Polo, M., 2019. Convergence of european natural gas prices. Energy Economics 81, 793–811.

Bianco, V., Scarpa, F., Tagliafico, L.A., 2015. Current situation and future perspectives of european natural gas sector. Frontiers in Energy 9, 1–6.

Broadstock, D.C., Li, R., Wang, L., 2020. Integration reforms in the european natural gas market: A rolling-window spillover analysis. Energy Economics 92, 104939.

Brons, M., Kalantzis, F., Vergano, L., 2019. Market Functioning & Market Integration in EU Network Industries â€"Telecommunications, Energy & Transport. Technical Report. Directorate General Economic and Financial Affairs (DG ECFIN), European ....

Caldara, D., Iacoviello, M., 2022. Measuring geopolitical risk. American Economic Review 112, 1194–1225.

Chen, Y., Wang, C., Zhu, Z., 2022. Toward the integration of european gas futures market under covid-19 shock: A quantile connectedness approach. Energy Economics 114, 106288.

Council of the European Union, 2022. Council adopts regulation on gas storage. URL: https://www.consilium.europa.eu/en/press/press-releases/2022/06/27/council-adopts-regulation-gas-storage/#:~:text=The%20regulation%20provides%20that%20underground,before%20the%20following%20winter%20periods.. accessed: 2024-06-13.

D'Agostino, R.B., 1970. Transformation to normality of the null distribution of g1. Biometrika , 679–681.

Demir, O., Demir, O., 2020. Natural gas market liberalisation in the context of the eu. Liberalisation of Natural Gas Markets: Potential and Challenges of Integrating Turkey into the EU Market , 63–102.

Diebold, F.X., Yilmaz, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal 119, 158–171.

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of forecasting 28, 57–66.

Diebold, F.X., Yılmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of econometrics 182, 119–134.

Ding, Z., Granger, C.W., Engle, R.F., 1993. A long memory property of stock market returns and a new model. Journal of empirical finance 1, 83–106.

EEX, 2023. European energy exchange newsroom. URL: https://www.eex.com/en/newsroom/detail?tx_news_pi1%5Baction%5D=detail&tx_news_pi1%5Bcontroller%5D=News&tx_news_pi1%5Bnews%5D=7321&cHash=8601dc6293eaee322feaea70e61ef96e. accessed: 2023-06-17.

Eurostat, 2023. Natural gas consumption statistics. URL: https://ec.europa.eu/eurostat/databrowser/view/nrg_cb_gas/default/table?lang=en&category=nrg.nrg_quant.nrg_quanta.nrg_cb. accessed: 2023-06-09.

Farag, M., Jeddi, S., Kopp, J.H., 2023. Global natural gas market integration in the face of shocks: Evidence from the dynamics of European, Asian, and US gas futures prices. Technical Report. EWI Working Paper.

Farag, M., Zaki, C., 2024. On the economic and political determinants of trade in natural gas. The World Economy 47, 806–836.

Finon, D., Romano, E., 2009. Electricity market integration: Redistribution effect versus resource reallocation. Energy Policy 37, 2977–2985.

Forsberg, L., Ghysels, E., 2007. Why do absolute returns predict volatility so well? Journal of Financial Econometrics 5, 31–67.

Fulwood, M., Sharples, J., Henderson, J., 2022. Ukraine Invasion: What This Means for the European Gas Market. The Oxford Institute for Energy Studies.

Garaffa, R., Szklo, A., Lucena, A.F., Féres, J.G., 2019. Price adjustments and transaction costs in the european natural gas market. The Energy Journal 40, 171–188.

Gas Infrastructure Europe, 2022. Aggregated Gas Storage Inventory (AGSI+). https://agsi.gie.eu/data-overview/DE.

Genizi, A., 1993. Decomposition of r 2 in multiple regression with correlated regressors. Statistica Sinica , 407–420.

Growitsch, C., Nepal, R., Stronzik, M., 2015. Price convergence and information efficiency in german natural gas markets. German Economic Review 16, 87–103.

Gugler, K., Haxhimusa, A., Liebensteiner, M., 2018. Integration of european electricity markets: Evidence from spot prices. The Energy Journal 39, 41–66.

Heather, P., 2021. European traded gas hubs: German hubs about to merge. 170, OIES Paper: NG.

Heather, P., 2022. A series of unfortunate events: Explaining european gas prices in 2021–the role of the traded gas hubs. Oxford Institute for Energy Studies, March .

Heather, P., 2023. European traded gas hubs: Their continued relevance. 183, OIES Paper: NG.

Heather, P., 2024. European traded gas hubs: the markets have rebalanced. Technical Report. OIES Paper: NG.

Hulshof, D., Van Der Maat, J.P., Mulder, M., 2016. Market fundamentals, competition and natural-gas prices. Energy policy 94, 480–491.

Huszár, Z.R., Kotró, B.B., Tan, R.S., 2023. Dynamic volatility transfer in the european oil and gas industry. Energy Economics 127, 107052.

IEA, 2020. Fast-tracking gas market reforms. URL: https://www.iea.org/commentaries/fast-tracking-gas-market-reforms. international Energy Agency. Accessed: September 21, 2024.

IEA, 2020. Gas 2020. URL: https://www.oecd-ilibrary.org/content/publication/df4b275f-en, doi:https://doi.org/https://doi.org/10.1787/df4b275f-en.

IEA, 2023. Gas Market Report Q1 2023. URL: https://www.iea.org/reports/gas-market-report-q1-2023.

IGU, I.G.U., 2022. Wholesale gas price survey 2023 edition - international gas union.

Jaeck, E., Lautier, D., 2016. Volatility in electricity derivative markets: The samuelson effect revisited. Energy Economics 59, 300–313.

Jarque, C.M., Bera, A.K., 1980. Efficient tests for normality, homoscedasticity and serial independence of regression residuals. Economics letters 6, 255–259.

Khalfaoui, R., Hammoudeh, S., Rehman, M.Z., 2023. Spillovers and connectedness among brics stock markets, cryptocurrencies, and uncertainty: Evidence from the quantile vector autoregression network. Emerging Markets Review 54, 101002.

Liu, J., Julaiti, J., Gou, S., 2024. Decomposing interconnectedness: A study of cryptocurrency spillover effects in global financial markets. Finance Research Letters 61, 104950.

Longstaff, F.A., 2010. The subprime credit crisis and contagion in financial markets. Journal of financial economics 97, 436–450.

Mensi, W., Boubaker, F.Z., Al-Yahyaee, K.H., Kang, S.H., 2018. Dynamic volatility spillovers and connectedness between global, regional, and gipsi stock markets. Finance Research Letters 25, 230–238.

Naeem, M.A., Chatziantoniou, I., Gabauer, D., Karim, S., 2024a. Measuring the g20 stock market return transmission mechanism: Evidence from the r2 connectedness approach. International Review of Financial Analysis 91, 102986.

Naeem, M.A., Gul, R., Shafiullah, M., Karim, S., Lucey, B.M., 2024b. Tail risk spillovers between shanghai oil and other markets. Energy Economics 130, 107182.

Neumann, A., Cullmann, A., 2012. What's the story with natural gas markets in europe? empirical evidence from spot trade data, in: 2012 9th international conference on the European energy market, IEEE. pp. 1–6.

Papież, M., Rubaszek, M., Szafranek, K., Śmiech, S., 2022. Are european natural gas markets connected? a time-varying spillovers analysis. Resources Policy 79, 103029.

Parkinson, M., 1980. The extreme value method for estimating the variance of the rate of return. Journal of business , 61–65.

Robinson, T., 2007. Have european gas prices converged? Energy Policy 35, 2347–2351.

Ruhnau, O., Stiewe, C., Muessel, J., Hirth, L., 2023. Natural gas savings in germany during the 2022 energy crisis. Nature Energy 8, 621–628.

Szafranek, K., Papież, M., Rubaszek, M., Śmiech, S., 2023. How immune is the connectedness of european natural gas markets to exceptional shocks? Resources Policy 85, 103917.

Taylor, S.J., 2008. Modelling financial time series. world scientific.

Valenti, D., 2022. Modelling the global price of oil: Is there any role for the oil futures-spot spread? The Energy Journal 43, 41–66.

Online Appendix

A. Descriptive statistics for NWE gas prices

Table A.1 presents descriptive statistics for the natural gas price data. The mean prices of the gas benchmarks are relatively close, with THE having the highest mean price and NBP the lowest. The standard deviations reveal significant volatility across all series, with THE exhibiting the highest volatility and NBP the lowest. Results of the Augmented Dickey-Fuller (ADF) unit root test indicate that none of the series is stationary. The minimum and maximum values show that TTF has the broadest price range, while ZTP has the narrowest.

Table A.1: Descriptive statistics for NWE gas benchmarks

	TTF	THE	NBP	ZTP
Mean	47.590	47.948	39.063	43.285
SD	49.909	50.006	35.444	41.148
Minimum	3.100	3.670	3.251	2.904
Maximum	330	315.130	227.796	249.116
Skewness	2.013^{a}	1.981^{a}	1.828^{a}	1.701^{a}
	(0.000)	(0.000)	(0.000)	(0.000)
kurtosis	7.612^{a}	7.347^{a}	6.981^{a}	6.197^{a}
	(0.000)	(0.000)	(0.000)	(0.000)
JB	2031.977^{a}	1874.907^{a}	1583.369^{a}	1181.495^{a}
	(0.000)	(0.000)	(0.000)	(0.000)
ADF	-2.365	-2.380	-3.140	-2.605

Note: The Mean represents the average value of the four gas benchmarks in levels (Euro/MWh). The other descriptive statistics are based on the return series of these price series. Skewness and Kurtosis are based on the tests by D'Agostino (1970) and Anscombe and Glynn (1983), respectively. JB refers to the Jarque-Bera normality test (Jarque and Bera, 1980). ADF is the Augmented Dickey-Fuller unit root test. ^{a} denotes significance at the one percent level, with values in parentheses representing p-values.

B. Averaged connectedness measures and interpretation

B.1. Averaged return connectedness measures

Table A.2 presents the averaged connectedness measures among the four return series throughout the sample period. Specifically, the table provides the overall R^2 decomposed measures, with the values in parentheses specifying contemporaneous and lagged R^2 decomposed measures, respectively. The 'FROM' column represents the total directional connectedness 'from' other variables in the system to the specific variable, measuring the extent to which a variable is influenced by shocks from all other variables. Similarly, the 'TO' row represents the total directional connectedness to other variables from the specific variables, indicating the influence of one benchmark on the rest of the variables in the system. The 'NET' row represents net connectedness, calculated as the difference between 'TO' and 'FROM' for each variable. Therefore, positive NET values indicate that the variable is a net transmitter of shocks (i.e., it influences other variables more than it is influenced), whereas negative NET values indicate that the variable is a net receiver of shocks (i.e., it is influenced more by other variables than it influences them). Finally, the 'TCI' value at the bottom of the last column represents the total connectedness in this network, with higher values suggesting a higher level of interconnectedness among the variables.

Table A.2: Averaged connectedness of return series

	TTF	**THE**	**ZTP**	**NBP**	**FROM**
TTF	2.17 [0.00, 2.17]	36.72 [35.63, 1.09]	27.25 [26.24, 1.01]	18.26 [17.44, 0.82]	82.23 [79.32, 2.91]
THE	36.99 [34.83, 2.16]	2.21 [0.00, 2.21]	25.20 [23.91, 1.30]	18.24 [17.02, 1.22]	80.44 [75.75, 4.68]
ZTP	27.35 [26.35, 1.00]	24.92 [24.13, 0.79]	1.10 [0.00, 1.10]	20.91 [20.21, 0.71]	73.18 [70.69, 2.50]
NBP	18.38 [17.65, 0.72]	17.95 [17.37, 0.58]	21.68 [20.79, 0.89]	1.76 [0.00, 1.76]	58.00 [55.81, 2.19]
TO	82.73 [78.84, 3.89]	79.58 [77.13, 2.45]	74.13 [70.93, 3.20]	57.41 [54.66, 2.75]	**TCI** [TCI^c, TCI^l]
NET	0.50 [-0.48, 0.97]	-0.85 [1.38, -2.23]	0.95 [0.25, 0.70]	-0.59 [-1.15, 0.56]	73.46 [70.39, 3.07]

Notes: R^2 decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one (BIC). Values in parentheses represent contemporaneous and lagged effects, respectively.

The results reveal that the TCI is 73.46%, indicating that, on average, 73.90% of the variance in each gas benchmark's returns can be explained by changes in the returns of other benchmarks within the network. A decomposition of contemporaneous and lagged components shows that contemporaneous interactions are the dominant factor, contributing 70.39%, while lagged interactions account for only 3.07%. This decomposition highlights that immediate temporal dynamics are the primary drivers of overall connectedness, while the impact of lagged effects is minor. Similarly, all contemporaneous 'FROM' and 'TO' connectedness measures are substantially higher than their lagged counterparts. Also, the 'FROM' column reveals that NBP has the lowest value at 58.00%, implying it receives the least amount of shocks from other benchmarks. Likewise, the 'TO' row indicates that NBP also has the lowest spillover contribution to others at 57.41%, underscoring its relatively isolated position within the network of benchmarks. Lastly, the 'NET' row shows that both THE and NBP are net receivers of return spillovers, with net connectedness values of -0.85% and -0.59%, respectively. This contrasts with TTF and ZTP, which exhibit positive net connectedness, indicating that these benchmarks are net transmitters of shocks.

B.2. Averaged volatility connectedness measures

Similar to the previous subsection, Table A.3 presents averaged connectedness measures for volatility. The TCI is 53.62%, implying that the explanatory power of the TCI accounts for 53.62% of the variance in each gas benchmark's volatility within the network. By decomposing this metric into its contemporaneous and lagged components, we observe that about 50.38% is caused by contemporaneous dynamics while only 3.24% is related to lagged interdependencies. The results also show that NBP exhibits the highest own volatility contribution at 2.38%, indicating that a significant portion of its volatility is self-explained. In contrast, the own volatility contributions for TTF and THE are much smaller (0.78% and 0.87%, respectively), indicating that these benchmarks' volatility is largely influenced by spillovers from each other. Analyzing the 'FROM' column and 'TO' row shows that NBP has the lowest values at 41.19% and 40.13%, respectively, highlighting its relatively isolated position within the network of benchmarks. Lastly, the 'NET' row shows that NBP is a net receiver of volatility spillovers, with a net connectedness value of -1.07%. This negative value contrasts with TTF, ZTP, and THE, which either exhibit positive net connectedness or are closer to zero, indicating that these benchmarks are net transmitters or more balanced in their spillover dynamics. Overall, from a static perspective, the analysis underscores NBP's unique position as a relatively self-contained benchmark with minimal influence on, and from, the other gas benchmarks.

Table A.3: Averaged connectedness of volatility series

	TTF	**THE**	**ZTP**	**NBP**	**FROM**
TTF	0.78 [0.00, 0.78]	32.78 [31.73, 1.05]	17.91 [16.67, 1.25]	12.95 [12.13, 0.82]	63.64 [60.53, 3.11]
THE	32.88 [31.83, 1.06]	0.87 [0.00, 0.87]	15.71 [14.33, 1.38]	13.82 [13.10, 0.71]	62.41 [59.26, 3.15]
ZTP	18.19 [17.03, 1.16]	15.67 [14.40, 1.27]	2.25 [0.00, 2.25]	13.36 [12.09, 1.27]	47.22 [43.52, 3.70]
NBP	13.20 [12.36, 0.84]	14.34 [13.51, 0.82]	13.66 [12.33, 1.33]	2.38 [0.00, 2.38]	41.19 [38.20, 2.99]
TO	64.27 [61.22, 3.05]	62.79 [59.64, 3.15]	47.29 [43.34, 3.95]	40.13 [37.33, 2.80]	**TCI** [TCI^c, TCI^l]
NET	0.63 [0.68, -0.06]	0.37 [0.37, 0.00]	0.07 [-0.18, 0.25]	-1.07 [-0.87, -0.19]	53.62 [50.38, 3.24]

Notes: R^2 decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one (BIC). Values in parentheses represent contemporaneous and lagged effects, respectively.

C. Robustness Checks

This section presents robustness checks to validate the baseline analysis. Specifically, three exercises are performed: first, using different rolling window sizes; second, replacing Pearson correlation coefficients with Spearman correlation coefficients; and finally, employing the range volatility measure of Parkinson (1980) as a proxy for volatility, instead of using absolute returns.

C.1. Robustness of connectedness measures to rolling window sizes

This subsection assesses the sensitivity of the connectedness measures to varying rolling window sizes. Specifically, we investigate the time-varying total return and volatility spillover indices using the R^2

decomposed connectedness approach for three different rolling window lengths (150, 200, and 250 days), with 200 days being the window size used in the baseline analysis. Figures A1(a) and A1(b) indicate that the estimates of the time-varying total spillover indices remain both qualitatively and quantitatively stable across different window sizes, reinforcing the validity of our initial empirical results.

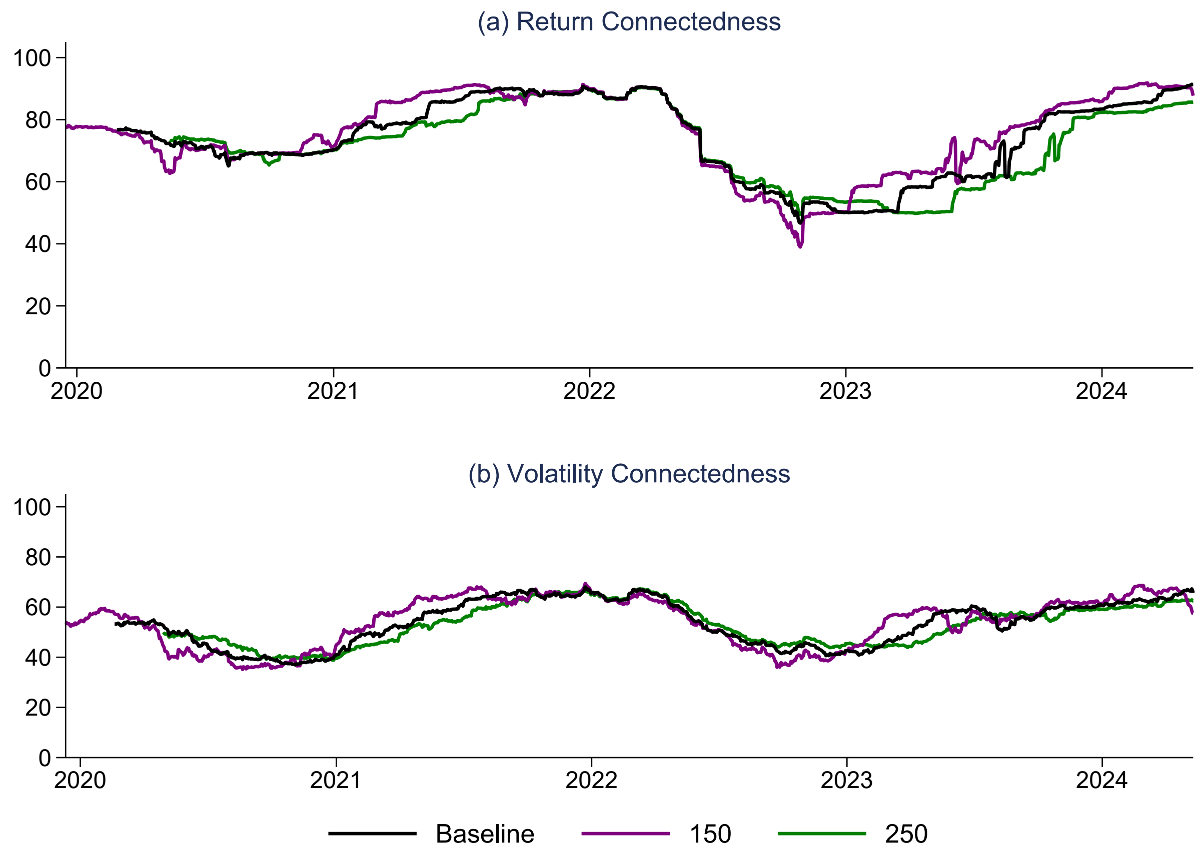

Figure A1: Connectedness with different rolling window sizes (150, 200, 250) for return and volatility series
Notes: R^2 decomposed measures are based on a 150, 200, and 250-day rolling-window VAR model with a lag length of order one (BIC).

C.2. Robustness of connectedness measures to correlation coefficients

This subsection replaces the Pearson correlation coefficients with Spearman correlation coefficients. The Spearman correlation is a non-parametric measure, less sensitive to outliers. The results, presented in Figures A2(a) for return series and A2(b) for volatility series, indicate that the findings are quantitatively similar to the baseline results, demonstrating robustness to the choice of correlation measure.

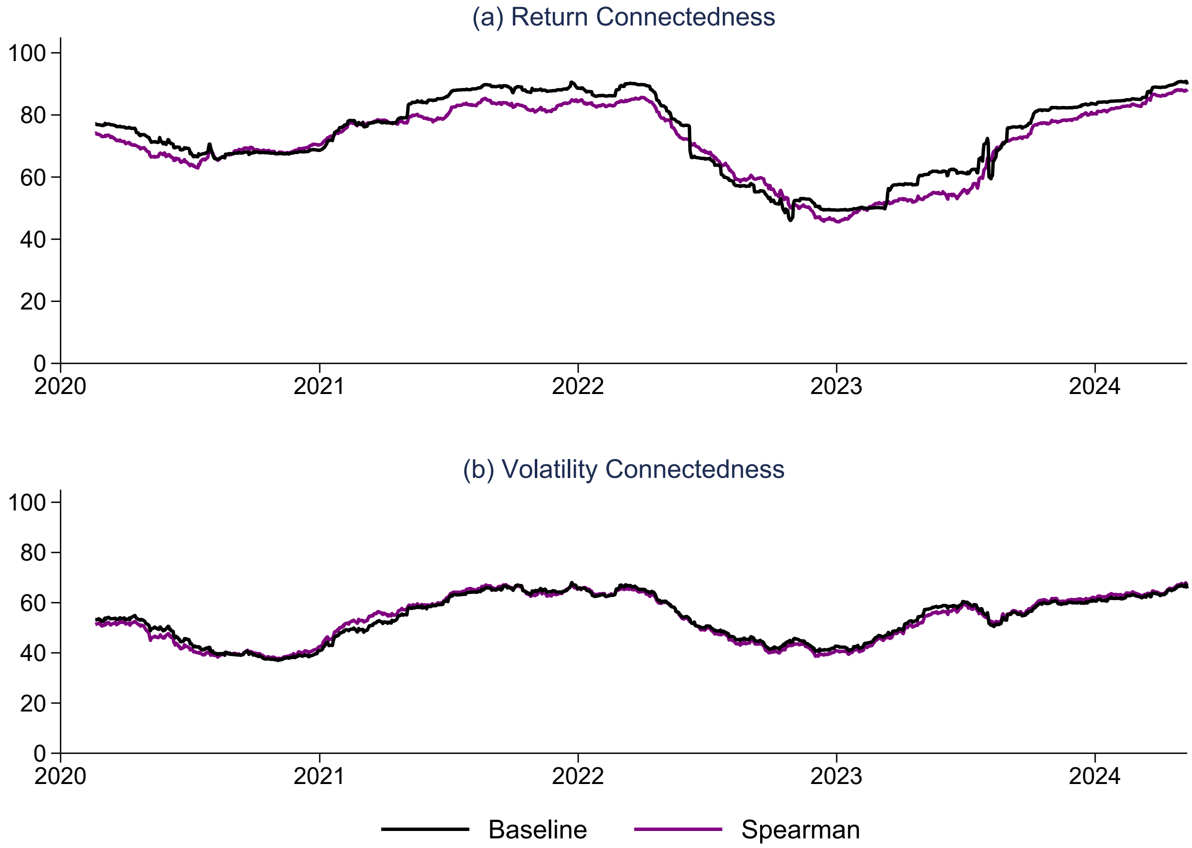

Figure A2: Connectedness using Spearman correlation coefficient for return and volatility series
Notes: R^2 decomposed measures are based on a 200-day rolling-window VAR model with a lag length of order one (BIC).

C.3. Robustness of volatility connectedness to a different volatility measure

This subsection analyzes volatility connectedness using the range volatility measure as proposed by Parkinson (1980). Following Alizadeh et al. (2002) and Diebold and Yilmaz (2012), weekly range volatility is calculated by:

$$Volatility_{Range} = 0.361 \times \left[\ln\left(P_t^{\max}\right) - \ln\left(P_t^{\min}\right)\right]^2 \tag{A1}$$

where $P_t^{\max}$ is the maximum price in week t, and $P_t^{\min}$ is the minimum price.

The intuition behind this approach is to examine the robustness of the conclusion regarding the dominance of contemporaneous effects on volatility connectedness, as found in the baseline analysis that uses absolute returns as a proxy for volatility. Additionally, this approach allows us to assess the robustness of the overall patterns of volatility connectedness during the examined shocks.

The results of the overall volatility index and its decomposition are presented in Figure A3, while the results of the directional connectedness are presented in Figure A4. Overall, the conclusions from this analysis, using this realized volatility measure, are consistent with those obtained in the baseline analysis of volatility connectedness.

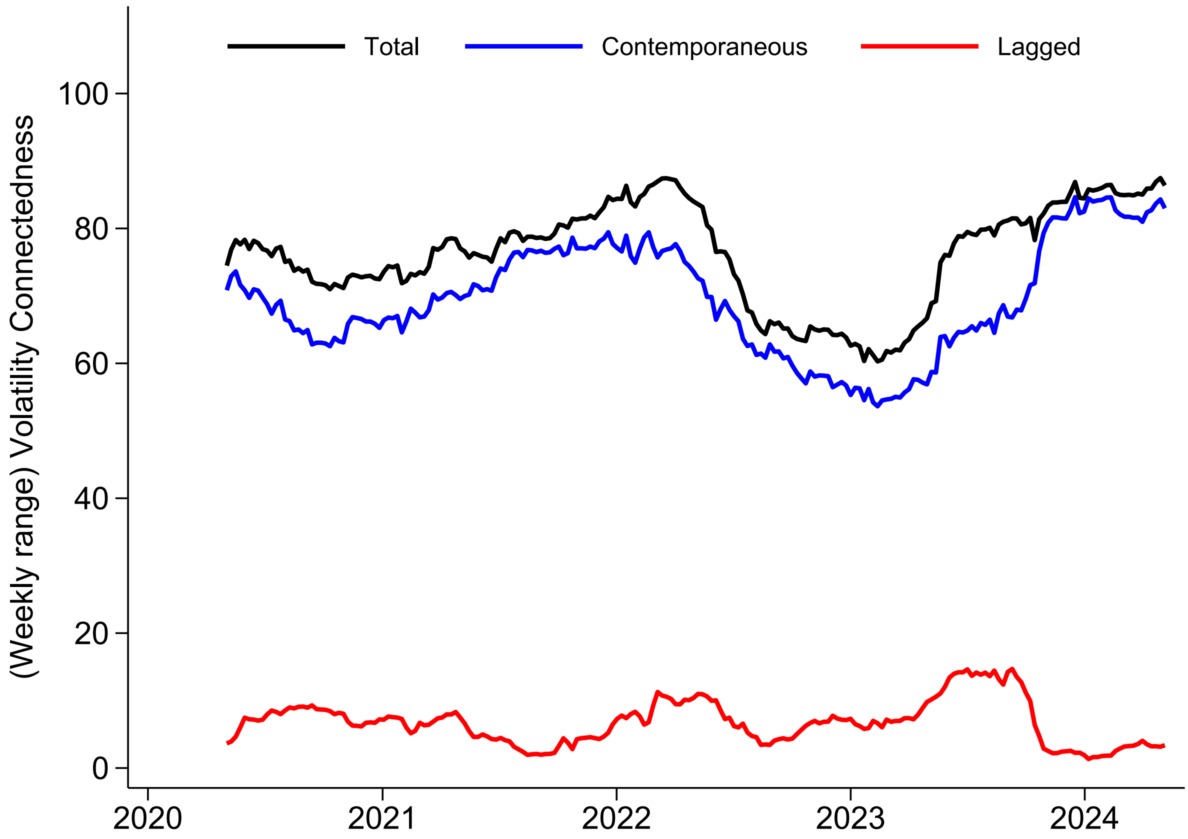

Figure A3: Dynamic total connectedness of realized weekly volatility series

Notes: R^2 decomposed measures are based on a 52-week (one year) rolling-window rolling-window VAR model with a lag length of order one.

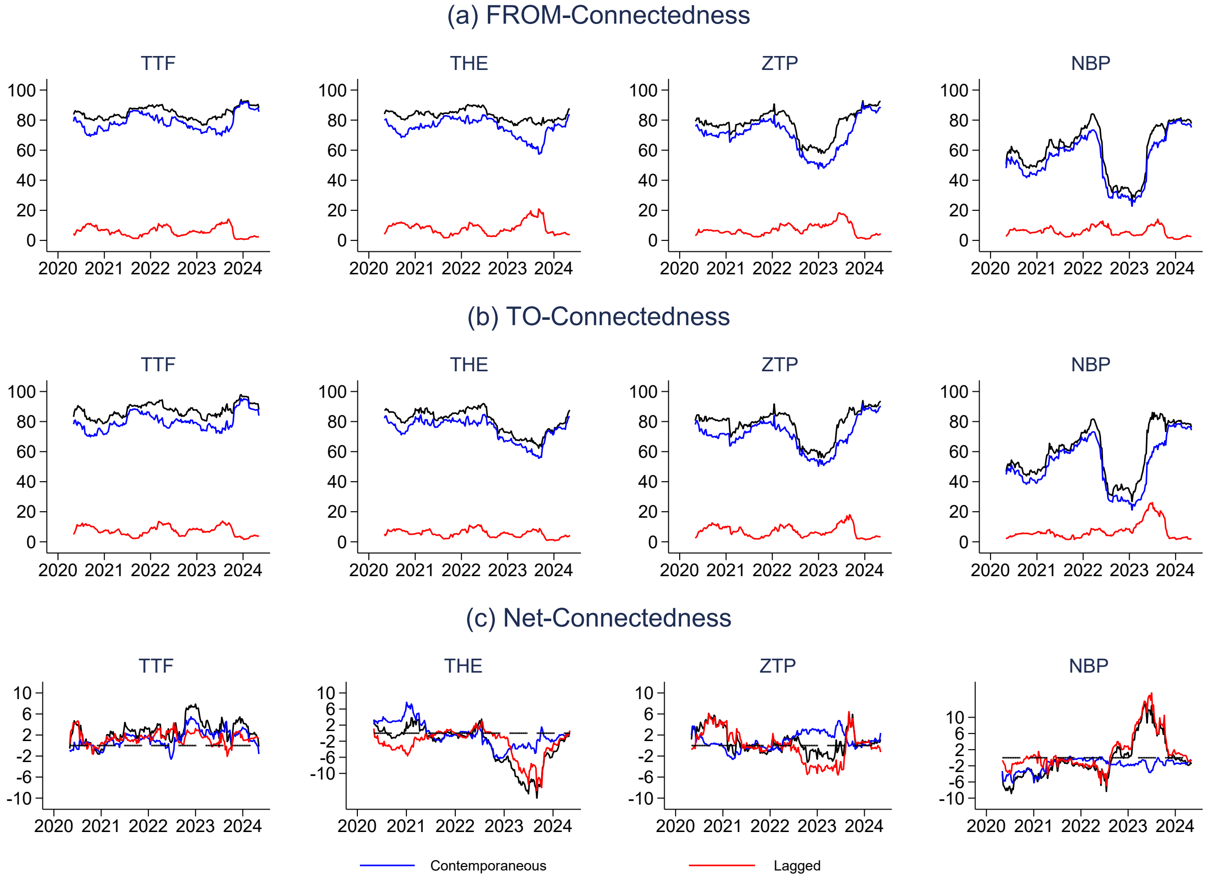

Figure A4: Dynamic directional connectedness of realized weekly volatility series

Notes: R^2 decomposed measures are based on a 52-week (one year) rolling-window rolling-window VAR model with a lag length of order one.

D. Additional results: connectedness analysis of NWE gas benchmarks using futures prices

The 'From' and 'To' directional connectedness for return and volatility series for futures prices are presented in Figures A5 and A7 respectively. The results indicate that spot and futures prices exhibit similar connectedness levels for these indices, except for NBP, where the 'From' and 'To' connectedness values for futures are relatively higher and more stable compared to those of spot prices throughout the entire period. This seems plausible, as our previous analyses show that the decoupling of NBP drives the low connectedness of spot prices across NWE. The net total directional connectedness analysis (Figures A5(c) for return series) shows that for THE and TTF, spot and futures prices generally share the same connectedness direction, except from the second half of 2022 to the first half of 2023. During this period, TTF futures are positive (transmitting shocks), while spot prices are negative (receiving shocks). Conversely, for THE, spot prices are positive while futures are negative. This highlights the different roles and reactions of futures and spot markets for these two benchmarks during stress periods. For ZTP, spot and futures net connectedness align except from the second half of 2021 to the second half of 2022. NBP also shows consistent net connectedness direction for both spot and futures prices except during the second half of 2020 and the first half of 2023. On the other hand, the net total directional connectedness analysis (Figures A7(c) for volatility series) shows that net connectedness estimated with spot and futures prices has the same sign throughout the entire investigated period. This suggests that both spot and futures markets for these benchmarks respond to and transmit volatility, driven by market uncertainty and risk, in the same manner through both stable and volatile periods.

D.1. Return connectedness analyses

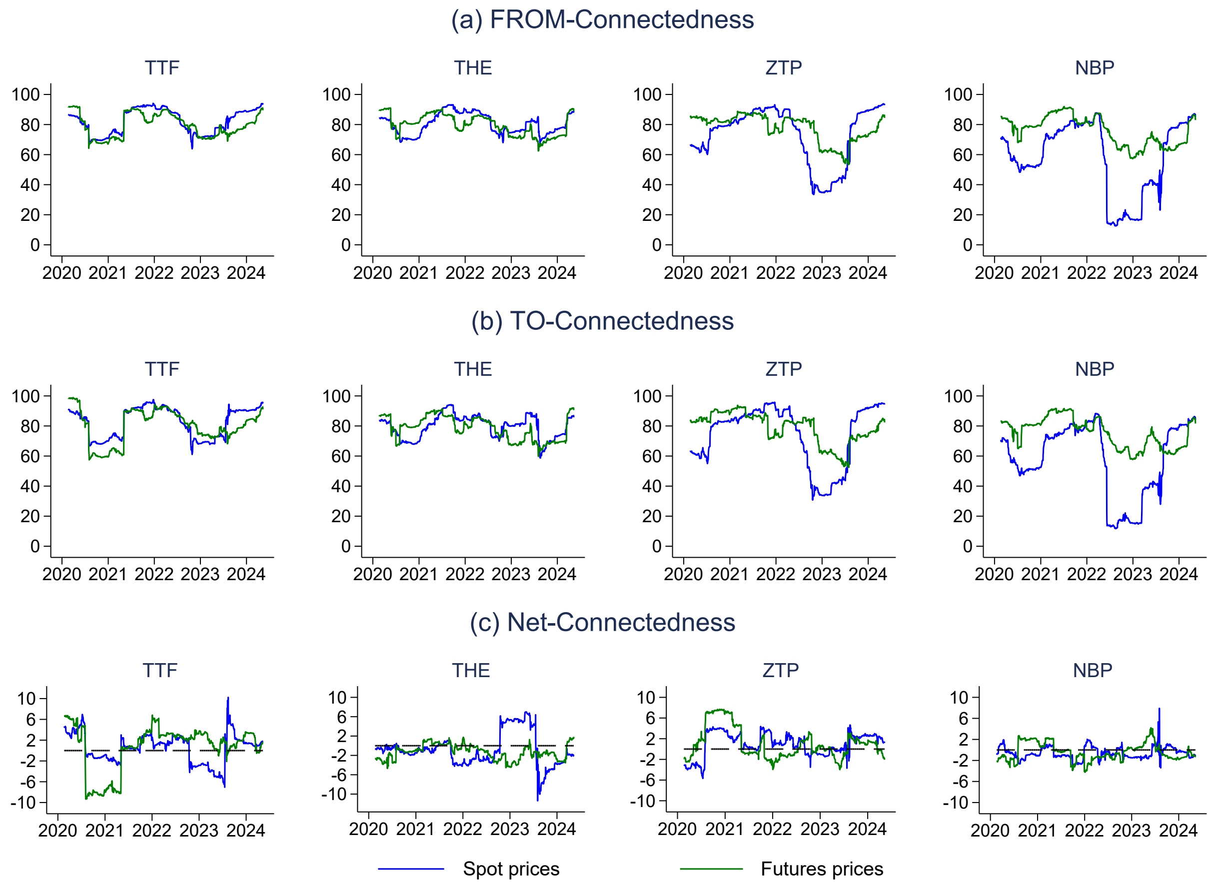

Figure A5: Comparison of directional connectedness indices: spot prices vs. futures prices

Notes: R^2 decomposed measures are based on a 200-day rolling-window rolling-window VAR model with a lag length of order one. These lines represent the total connectedness index. The contemporaneous and lagged connectedness are removed to facilitate comparison, but they show the same pattern as observed in the baseline results.

D.2. Volatility connectedness analyses

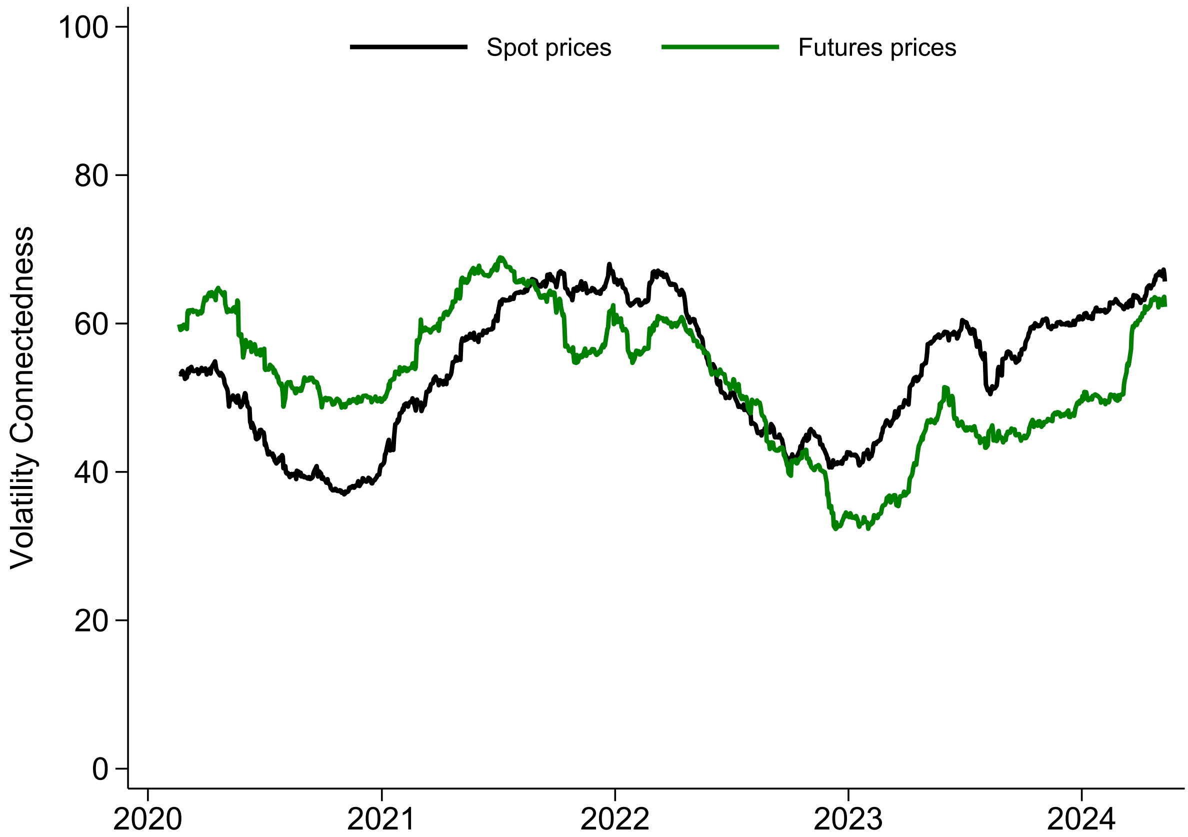

Figure A6: Dynamic total connectedness of volatility series using futures prices

Notes: R^2 decomposed measures are based on a 200-day rolling-window rolling-window VAR model with a lag length of order one. These lines represent the overall connectedness index. The contemporaneous and lagged connectedness are removed to facilitate comparison, but they show the same pattern as observed in the baseline results.

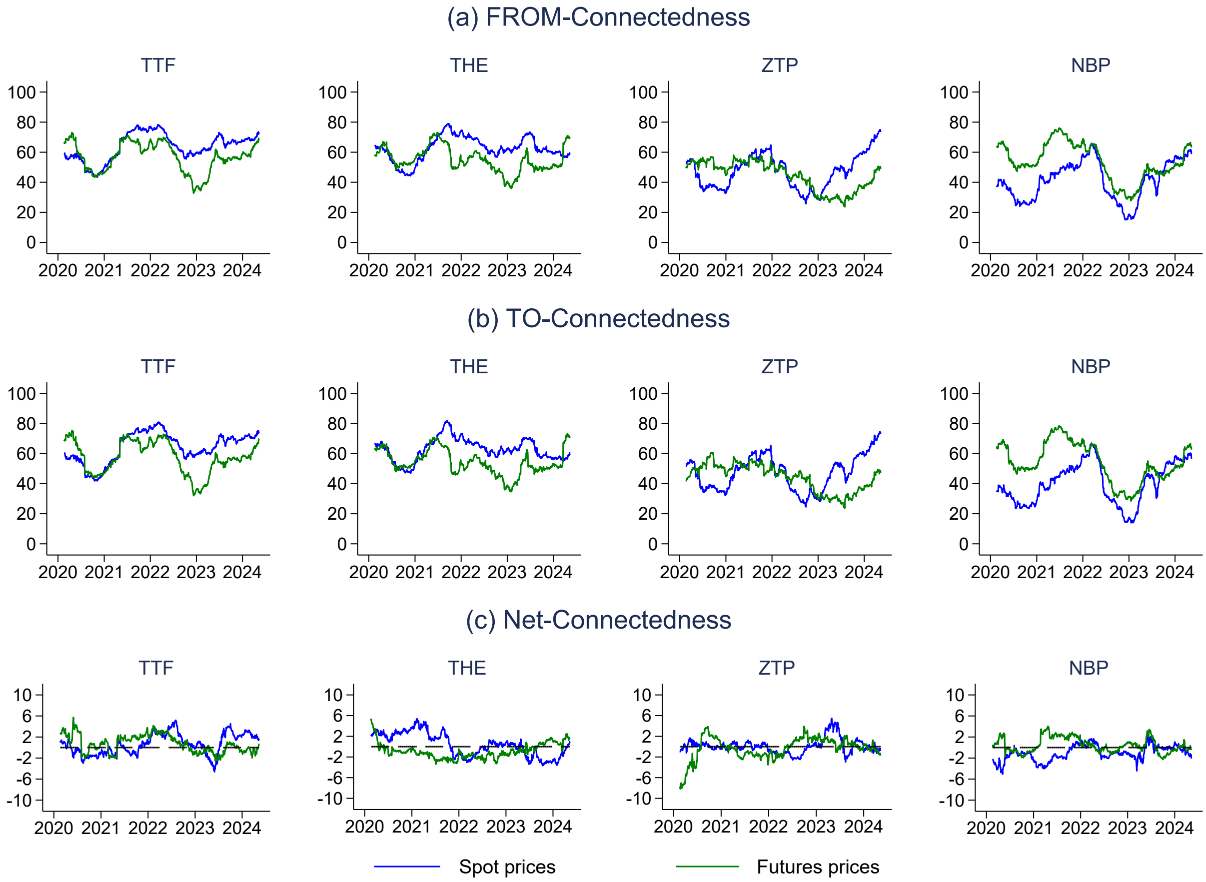

Figure A7: Dynamic directional connectedness of volatility series using futures prices

Notes: R^2 decomposed measures are based on a 200-day rolling-window rolling-window VAR model with a lag length of order one. These lines represent the total connectedness index. The contemporaneous and lagged connectedness are removed to facilitate comparison, but they show the same pattern as observed in the baseline results.

E. Additional results: the relationship between infrastructure congestion and gas market volatility connectedness in NWE

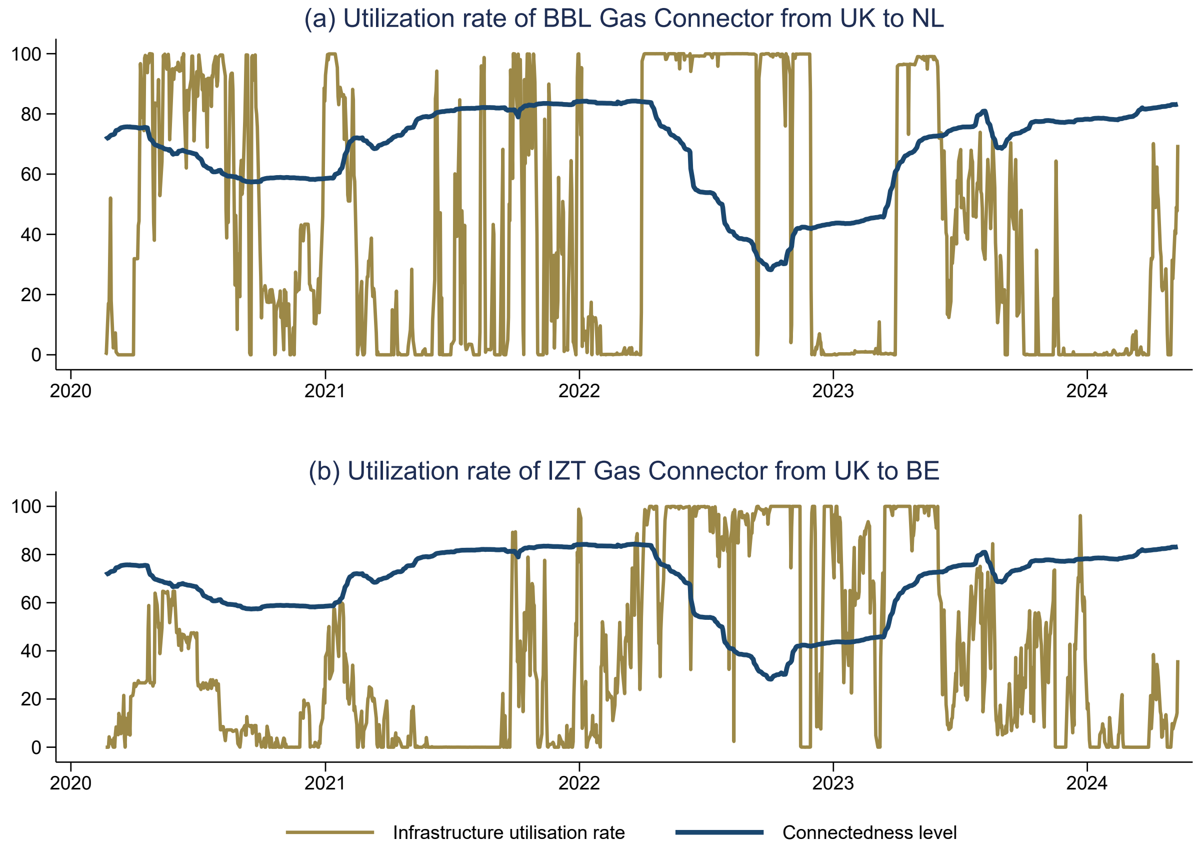

Figure A8: volatility connectedness level and utilization rate of BBL and IZT gas pipelines

Notes: Data on the utilization rates are obtained from the ENTSOG Transparency Platform. The solid line represents the volatility connectedness between the NWE gas benchmarks, as analyzed in Subsection 5.2. Values on the vertical axis are expressed as percentages (%). BBL refers to the Balgzand-Bacton Line pipeline, and IZT refers to the Interconnector Zeebrugge Terminal pipeline. Country abbreviations: UK (United Kingdom), NL (Netherlands), and BE (Belgium).