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Global Natural Gas Market Integration in the Face of Shocks: Evidence from the Dynamics of European, Asian, and US Gas Futures Prices †

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Abstract

This paper analyzes the integration of the American, European, and Asian natural gas markets over the period 2016-2022, with a focus on how the demand shock caused by the COVID-19 pandemic and the supply shock caused by geopolitical tensions in the European market affected this integration. We also examine which regional market is leading in reflecting new information and shocks into the market price. Our analysis indicates that the market integration process has been impacted by external shocks, leading to a decrease in the degree of integration between the European and Asian markets. Additionally, we find that the American market is no longer integrated with the other two markets after the supply shock, potentially due to the US's congested and fully utilized LNG infrastructure. Our analysis also shows that the gas price differentials adjust asymmetrically in response to disturbances, suggesting that markets respond differently to positive and negative shocks. Moreover, we show that the lead/lag relationship changes over time and exhibits a dynamic behavior. Finally, we discuss the fundamental changes in the global gas market that align with our empirical results.

Keywords: Natural gas markets; Market integration; Threshold Co-integration; Time-varying causality
JEL classification: C32, D40, D58, F21, F41, G13, G14, L95, Q35, Q41.

1. Introduction

International trade in natural gas is divided into three main regional markets: Asia, Europe, and North America. This segmentation has been established due to the limited Liquefied Natural Gas (LNG) transportation capacities among the three regions. However, the literature suggests that these markets are gradually becoming more integrated (Neumann, 2009; Li et al., 2014). Market integration refers to the

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extent to which price shocks in one region are transmitted to other regions (McNew and Fackler, 1997; Fackler and Goodwin, 2001). Investigating this hypothesis has implications for the security of supply, as importers in one region must take into account market circumstances in other regions to ensure their own security of supply.

The integration process among the three regional gas markets is facilitated by different drivers. First, there has been surplus natural gas production in some regions, while the gas is consumed in other regions.[1] This has necessitated the development of the international trade of gas, with LNG trade emerging as a key solution to this problem. Meanwhile, decreasing shipping costs and growing export capacities have significantly increased the technical and economic possibilities for trade between regions (IEA, 2020a). This has made it more feasible and cost-effective for gas to be transported across longer distances, enabling regional gas markets to become more integrated (e.g., Barnes and Bosworth, 2015; Li et al., 2014). Second, many commercial agreements have transitioned from traditional oil-indexed pricing of long-term contracts to an increase in the significance of hub-based pricing. For example, the Gas-on-Gas (G-o-G) competition[2] share of global gas consumption increased from 31% in 2005 to 49% in 2021, whereas the oil indexation share declined from 24% to 19% over the same period (IGU, 2021). The literature also suggests that the relationship between oil and natural gas prices has become more volatile over time, revealing the decoupling of the two commodities (Chiappini et al., 2019; Neumann, 2009). Meanwhile, the G-o-G has witnessed a growing share of the spot and short-term transactions, where regional supply and demand balance changes can encourage LNG exporters to redirect their spot volumes to other destinations (IGU, 2021). These changes have increased the liquidity of the global gas market, introduced a powerful tool for spatial arbitrage, and induced a growing presence of physical traders. Third, developing new exploration technologies for shale gas has fueled a rapid increase in production in North America, commonly referred to as the shale gas revolution (Melikoglu, 2014). As a result, the United States began exporting LNG in 2016 and has rapidly become a major player in the global market, with export capacities increasing year over year.[3] Fourth, international trade is currently motivated by supply diversification strategies that involve a mix of supply from pipelines and LNG. This is relevant because relying heavily on gas pipelines may lead to high transaction costs, such as the increased risk of breaching natural gas supply contracts. (Farag and Zaki, 2021; Ritz, 2019).

[1] Figure A.1 in the Appendix .1 compares the development of gas production and consumption between 2012 and 2022. It shows that production has significantly increased in export regions that do not have pipeline connections to the main gas import regions. This has been made possible by the export of LNG.

[2] Gas-on-Gas (G-o-G) competition means that the gas price is determined by the intersection of supply and demand and can be traded over different periods (daily, monthly, annually, or other periods). It comprises three mechanisms, namely trading (where trades occur at a physical or notional hub), bilateral (several buyers and sellers provide the competitive element), Spot and short-term LNG transactions (the price reflects the current supply-demand situation) (IGU, 2021; GIIGNL, 2022).

[3] For example, the U.S. expanded its LNG liquefaction terminals on a large scale from 16 bcm in 2016 to 131 bcm in 2022, accounting for 62% of the global increase in LNG liquefaction capacity Rystad Energy (2023).

However, the COVID-19 pandemic and geopolitical tensions in Europe have introduced uncertainties and disruptions in the demand and supply sides of the global gas market. In 2020, global natural gas demand decreased by over 82 billion cubic meters (bcm), representing a 2% decline compared to 2019, due to lockdown measures affecting economic activities, relatively mild temperatures during the winter of 2019-2020, and increased power generation from wind in Europe (IEA, 2020a; Rystad Energy, 2023). Consequently, underground and LNG storage facilities reached record highs at the end of winter 2019-2020. This led to an oversupply in the global natural gas market, resulting in historic low gas prices and short-term market uncertainty (IEA, 2020d). In the latter half of 2021, the European and Asian gas markets experienced a price rally due to the resurgence of demand from the industrial and heating sectors as economic activity rebounded and extreme weather events occurred. The situation was further exacerbated by geopolitical tensions (GPT) between Russia and its European trading partners. Starting in September 2021, Russia reduced daily gas flows to Europe to the level of nominations from long-term contracts, resulting in no additional gas volumes being made available to the European spot market (Fulwood et al., 2022). Meanwhile, a tightening LNG market resulted from planned and unplanned outages, unprecedented increases in charter rates, and global LNG infrastructures being operated at maximum capacity (IEA, 2023). Accordingly, these shocks are expected to impact the integration of the three regional gas markets by changing the market fundamentals in each region, altering their relative bargaining power in the global LNG market, and increasing the transaction costs[4] that could impede arbitrage activity.

Against this background, our study aims to answer two main questions: (1) How have the demand shock caused by the COVID-19 pandemic outbreak and the supply shock caused by GPT affected the global gas market integration?; and (2) Which regional market is leading in reflecting new information and shocks into the market price? Therefore, we aim to contribute to the literature in four ways. First, we analyze the global gas market integration over the period 2016-2022, allowing us to consider recent dynamics in this market, such as the rise of US LNG exports since 2016 and the market shocks caused by the COVID-19 pandemic and GPT. Second, we provide new findings on how those shocks affect the long-run relationship by conducting our empirical analysis over three sub-samples: the pre-pandemic period, the pandemic peak period, and the global geopolitical tensions period.[5] This allows us to examine how the degree of market integration has changed over our sample. Additionally, we investigate qualitatively the fundamental changes and factors in the global gas market that align with our empirical results. Third, we model the adjustment process using the threshold co-integration technique. This enables us to understand how gas price differentials adjust

[4]The transaction costs do not only include transport costs, but they also include temporal and indirect expenses related to the costs of searching for information, contract default risk, negotiating, legal duties insurance, policy uncertainty, and financing the trading process (Ihle and von Cramon-Taubadel, 2008).

[5]The "pre-pandemic period" refers to the time before the COVID-19 pandemic, the "pandemic peak period" refers to the time following the outbreak of the pandemic in March 2020, and the "global geopolitical tensions period" refers to the time following the start of geopolitical tensions in Europe in September 2021.

following a shock and to explicitly model the transaction costs that can impede arbitrage activity.[6] Fourth, we examine the dynamic causal relationships among the regional gas markets, which, to our knowledge, has not been done before. Specifically, we investigate whether the bidirectional causality in the global gas market could change over time and, thus, exhibit a dynamic behavior.

Our empirical analysis is based on the daily gas futures prices traded in the North American (Henry Hub, hereafter HH), European (Title Transfer Facility, hereafter TTF), and East Asian (East Asian Index, hereafter EAX) gas markets. We employ the threshold co-integration approach of Enders and Siklos (2001) to analyze the long-run relationship and use the time-varying causality method introduced by Shi et al. (2020) to examine the dynamic Granger causality relationship. Our findings can be summarized as follows. First, the long-run relationship and the associated error correction process exhibit different results for each sub-period and price pair. This implies that the market integration process in the global gas market has been affected by the investigated shocks. For instance, our results show that the degree of integration between the Asian and European markets decreased during the pandemic peak and global geopolitical tensions periods. Additionally, the American market is no longer integrated with the other two markets in the post-GPT period, possibly due to the congested and fully utilized LNG infrastructure. Second, we find that price differentials of the three price pairs adjust asymmetrically following a shock. This means that the adjustment process to the long-run equilibrium depends on whether the gas price spreads are increasing (i.e., widening) or decreasing (i.e., narrowing) from a certain threshold value, which we find to be relatively high in the second and third sub-samples. This finding suggests that transaction costs in the global gas market have increased following the respective shocks. Third, the Granger causality findings demonstrate that the price discovery process in the global gas market is dynamic. This means that the leading role played by each gas benchmark may change over time, depending on specific events or shocks in the corresponding region.

The rest of the paper is structured as follows. Section 2 provides an overview of the relevant literature. Section 3 outlines a conceptual background of our empirical analysis. Section 4 explains our econometric approach, and Section 5 describes our data. While Section 6 presents our results, Section 7 discusses qualitatively what has changed in the global gas market that would be consistent with these results. Finally, Section 8 concludes

2. Literature Review

The integration of the global gas market has been the subject of several studies, which suggest different levels of integration depending on the time period studied. These studies primarily rely on price data analysis to measure the degree of market integration, hypothesizing that a higher degree of convergence between gas

[6] See section 3.1 for more clarification on the rationale behind considering non-linearities in a spatial market integration setting.

prices signifies stronger spatial arbitrage and market integration. The most commonly used methodological approach to test this hypothesis is the co-integration technique, which examines the existence of a long-run relationship between prices.[7]

Siliverstovs et al. (2005) investigate the integration of North American, European, and Asian gas markets using monthly prices from 1990 to 2004. Their co-integration analysis provides evidence of integration between the Asian and European markets, while the North American market remains decoupled. The authors suggest that the limited effects of inter-continental trade may have contributed to the large market power of regional suppliers, thus hindering the integration of the North American market. A similar conclusion is also obtained by Li et al. (2014), who use a multivariate approach aimed at detecting convergence between the three markets from 1997 to 2011. They claim that the integration between the Asian and European markets is probably driven by the underlying pricing mechanism that is tied contractually to the oil price. Using the Kalman Filter technique, Neumann (2009) examines the impact of intercontinental arbitrage on price convergence in the Atlantic Basin. She uses daily price data from the UK (i.e., NBP), Belgium (i.e., Zeebrugge), and the US (i.e., Henry Hub) from 1999 to 2008. The findings show that the time-varying market integration coefficient moves to one for the NBP-Henry Hub and Zeebrugge-Henry Hub pairs. The study concludes that increasing the liquefaction capacities in either Europe or North America will enhance further arbitraging opportunities in the Atlantic basin.

However, Nick and Tischler (2014) point out that linear co-integration models may not accurately represent the dynamics of arbitrage in the global gas market, as they do not consider transaction costs, which can hinder arbitrage activity. Therefore, they investigate the degree of integration between Henry Hub and NBP through a threshold co-integration approach that can model these transaction costs. The results find strong evidence in favor of non-linearity in the investigated sub-samples (2000-2008 & 2009-2012), with high threshold estimates in the latter period indicating obstacles to arbitrage. More recently, Chiappini et al. (2019) use a non-linear co-integration approach with daily price data over the period 2004-2018, confirming the asymmetric convergence in the global gas market. Their analysis also shows that the degree of integration between the American and European regions has increased, whereas this is not the case between the American and Asian markets.

Our analysis is also related to another strand of literature that has explicitly focused on the analysis of the price discovery process. To date, few studies have examined this question in the natural gas markets, limiting their analysis to the inter-temporal context. For example, Nick (2016), Dergiades et al. (2012), and Gebre-Mariam (2011) rely on the theory of storage, which states that there is a relationship between spot and futures markets for storable commodities. Thus, they argue that the two markets are connected through

[7]For a detailed review of the different empirical methods employed to examine the degree of spatial integration of natural gas markets, see Dukhanina and Massol (2018).

transactions of market participants who optimize their portfolios inter-temporally. They conclude that price discovery generally occurs in the futures market. Nevertheless, empirical research on price discovery along the horizontal dimension of the gas market is rather scarce. The only study that focuses on this question so far is Park et al. (2008), analyzing the price discovery among eight North American natural gas spot market prices using the Vector Error Correction Model (VECM).

Three main points stand out from this literature review. First, the conclusion on the integration of the regional gas markets varies depending on the time period studied, reflecting that the market integration process in the gas market is time-varying. Second, LNG trade provides more opportunities for spatial arbitrage, leading to greater price convergence among the three regional markets. However, accurately modeling this convergence requires considering transaction costs and asymmetric dynamics in the adjustment process. Third, the price discovery process in the global gas market remains poorly examined and understood, particularly given recent dynamics in the market. Consequently, it remains unclear which regional benchmark plays the dominant role in the global gas market.

3. Conceptual Background

Before proceeding with our empirical analysis, we first provide a conceptual background of the market integration hypothesis and the gas pricing mechanisms. We incorporate these definitions in the remainder of the paper.

3.1. Market integration hypothesis

In the context of multiple markets for a certain commodity, market integration refers to how new information and shocks in one market are transmitted to the prices of other markets via an arbitrage mechanism. The definition of market integration was first introduced by Cournot, who stated that it is "an entire territory of which the parts are so united by the relations of unrestricted commerce that prices take the same level throughout with ease and rapidity" (Cournot, 1838). Empirical studies have examined the market integration hypothesis along vertical (i.e., prices at different stages of the supply chain), horizontal (i.e., prices between locations), and inter-temporal (i.e., prices of spot and futures markets) dimensions using co-integration methods and related forecasting techniques (e.g., impulse response functions) (Ihle and von Cramon-Taubadel, 2008; Roman and Žáková Kroupová, 2022). Our analysis focuses on the horizontal dimension of market integration, which is theoretically motivated by the Enke-Samuelson-Takayama-Judge spatial equilibrium model (Enke, 1951; Samuelson, 1952; Takayama and Judge, 1971). More concretely, this model provides two equilibrium conditions, which can be expressed as follows:

$$P_t^A - P_t^B \geq \tau \tag{1}$$

Equ.1 represents two alternative states of the market. The first one, which corresponds to strict equality, refers to the case where the price in two spatially separated markets should not differ by more than the transaction costs between them. The second state, which corresponds to inequality, refers to the case where rational traders will engage by shifting supply from market B to market A, causing P_t^A to decrease and P_t^B to increase. However, this state will only be achieved if the LNG infrastructure in market A is not congested. In other words, there are no arbitrage opportunities in the second case unless the LNG terminals are not fully utilized in the market with the higher price.[8] However, it should be noted that the price transmission process between Asia and Europe differs from that between the US and Asia and Europe. While the price transmission can occur through physical trade facilitated by a third party or a swing supplier[9], the transmission between American and the other two prices can happen through direct physical trade from the American to the European and Asian markets.

However, it should be noted that trade is neither necessary nor sufficient to achieve spatial market integration. This is because there are other mechanisms, such as information exchange among traders and suppliers (i.e., trader networks), through which price transmission may occur when trade flows do not exist. Therefore, access to new market information can affect the price expectations of spatial arbitrageurs and eliminate price differences across markets, even in the absence of physical trade activities (Stephens et al., 2012; Jensen, 2007).

3.2. Gas Pricing Mechanisms

The pricing mechanism is one of the key instruments in the gas market because it determines how changes in market fundamentals can be reflected in the price levels. The predominant price mechanisms in the gas market include oil price indexation and hub indexation (gas-to-gas competition). According to the oil indexation, natural gas prices are contractually linked to crude oil prices (mainly in Asia) or refined fuels prices (mainly in Europe). Based on the hub indexation, the gas price is competitively determined by the interplay between supply and demand. Other gas price mechanisms include bilateral monopoly (i.e., the price is determined bilaterally between a large seller and a large buyer) and different regulated gas prices (Hafner and Luciani, 2022; IGU, 2021).

The pricing mechanism in each region has distinctive characteristics. While the North American market totally follows hub-based pricing, the European and Asian markets historically relied on oil indexation. The rationale behind the oil indexation mechanism was that oil and natural gas were substitutes, especially in the electricity sector and heavy industries (Corbeau et al., 2016). However, changing regulatory settings and

[8] This was the case in the summer months of 2022 in the European gas market. Despite the relatively high price in the latter market, there were limited arbitrage opportunities because the LNG regasification terminals (e.g., the Gate terminal) were operating at their maximum capacity.

[9] A swing supplier, such as Qatar, is able to respond flexibly to unexpected shocks in the market and can reroute shipments based on current market conditions (Kim et al., 2020).

trading developments have made natural gas not directly compete with oil (Simkins et al., 2022). Therefore, the transition to a hub-based pricing mechanism has recently increased in Northwest Europe and East Asia. The transformation in Europe is basically motivated by market liberalization and competition policies (Simkins et al., 2022). Also, some East Asian countries, such as Japan, Singapore, and China, have already started to switch from the dominant oil-indexation mechanism to establish their own regional gas pricing benchmark (Wang et al., 2022; Shi and Variam, 2016). In this study, the scope of our analysis is limited to the hub-based pricing of natural gas. Specifically, we analyze the market integration hypothesis among the three trading hubs in the North American, European, and East Asian Markets.

4. Methodology

Our analysis primarily relies on the co-integration approach, commonly used to investigate price relationships. When two non-stationary price series have a stationary linear combination, they are considered co-integrated, indicating that the difference between the two price series is restricted by a long-term relationship resulting from arbitrage activities between markets. A primary co-integration method is the two-step procedure developed by Engle and Granger (1987), which assumes a symmetric relationship between variables. However, adjustments to the long-run equilibrium due to positive and negative divergences may take place at different speeds and, accordingly, can be asymmetric. This means that the conventional Engel and Granger co-integration test can be misspecified when the adjustment process is asymmetric or nonlinear.

To account for this nonlinearity, Enders and Granger (1998) and Enders and Siklos (2001) extend the threshold-autoregressive (TAR) and momentum-TAR tests for unit roots to a multivariate context, allowing for threshold co-integration testing. This approach has been widely used by several studies in the literature to test for asymmetric co-integration between energy price series (e.g., Hammoudeh et al., 2008; Ghoshray and Trifonova, 2014; Chiappini et al., 2019). In this study, we apply the threshold co-integration approach to evaluate the price dynamics in the global natural gas market, allowing for the assessment of the asymmetric price transmission process.

4.1. Linear co-integration analysis

We concentrate on examining the daily futures prices for three regional gas markets, North America, Europe, and East Asia. To determine their nonstationarity and integration order, we conduct three different unit root tests, namely Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS). If these tests indicate that the price series have a unit root, then the co-integration analysis is applied to assess their long-run relationship.

Engle and Granger (1987) propose a two-step approach that focuses on the time series property of the residuals from the long-term equilibrium relationship. Suppose P_t^A and P_t^B are price series that are stationary in the first difference (i.e., integrated of order one or I(1)). The first step is to estimate the following simple bi-variate equation using the Ordinary Least Squares (OLS):

$$P_t^A = \beta_0 + \beta_1 P_t^B + \varepsilon_t \tag{2}$$

where P_t^A and P_t^B are two gas price series in their logarithmic transformation, β_1 is the long-run coefficient of price transmission between the two prices, β_0 measures the margin between them, and ε_t is the error term. We estimate three sets of gas price pairs: (A,B) = (TTF, EAX); (HH, TTF); and (HH, EAX). In the second step, the estimated $\hat{\varepsilon}_t$ derived from Equ.2 are used to estimate the following procedure:

$$\triangle\hat{\varepsilon}_t = \rho\hat{\varepsilon}_{t-1} + \sum_{i=1}^{P} \varrho_i \triangle\hat{\varepsilon}_{t-i} + \mu_t \tag{3}$$

where $\hat{\varepsilon}_t$ represents a divergence from the long-run relationship. If the null hypothesis of $\rho = 0$ is rejected, this means that $\hat{\varepsilon}_t$ is stationary and the two price series P_t^A and P_t^B are linearly co-integrated. This is done by applying the Dickey-Fuller unit root test. The number of lags in Equ.3 is chosen using the Akaike Information Criterion (AIC) to avoid serial correlation in the residuals.

4.2. Threshold Co-integration analysis

The above Engle-Granger two-stage approach assumes that prices adjust symmetrically to deviations from the equilibrium, regardless of whether those deviations are positive or negative. As an alternative, the Enders and Siklos (2001) model extends the Engle and Granger (1987) co-integration approach by letting the divergence from the long run behave asymmetrically as follows:

$$\triangle\hat{\varepsilon}_t = \rho_1 I_t \hat{\varepsilon}_{t-1} + \rho_2(1 - I_t)\hat{\varepsilon}_{t-1} + \sum_{i=1}^{K} \vartheta_i \triangle\hat{\varepsilon}_{t-i} + \mu_t \tag{4}$$

$$I_t = 1 \quad \text{if} \quad \hat{\varepsilon}_{t-1} \geq \tau \quad \text{;and} \quad 0 \quad \text{otherwise} \tag{5a}$$

$$I_t = 1 \quad \text{if} \quad \triangle\hat{\varepsilon}_{t-1} \geq \tau \quad \text{;and} \quad 0 \quad \text{otherwise} \tag{5b}$$

where I_t is the Heaviside indicator, the coefficients ρ_1 and ρ_2 refer to the rate at which positive and negative divergences (or shocks) are adjusted, respectively, and K is the number of lags that is selected by the AIC to account for serially correlated residuals.

The Heaviside indicator I_t can be specified with two different definitions of the threshold variable: either the lagged residual ($\hat{\varepsilon}_{t-1}$) or the change of the lagged residual ($\triangle\hat{\varepsilon}_{t-1}$). Accordingly, Equations 4 and 5a refer to the Threshold Autoregression (TAR) model, whereas Equations 4 and 5b represent the Momentum Threshold Autoregression (MTAR) model. While the TAR model allows the degree of autoregressive decay to rely on the state of the residuals, the MTAR model allows the residuals to display differing amounts of autoregressive decay depending on whether they are increasing or decreasing. Thus, the latter can consider steep variations in the residuals when the adjustment is believed to exhibit more momentum in one direction than the other (Enders and Granger, 1998).

The threshold value (τ) can be set to zero since the regression deals with the residual series. Alternatively, Chan (1993) suggests a search method to obtain a consistent estimate of the threshold value that requires multiple steps. First, we sort the threshold variable (i.e., $\hat{\varepsilon}_{t-1}$ or $\triangle\hat{\varepsilon}_{t-1}$) in ascending order. Second, we apply a trim to the upper and lower end of the threshold variable to obtain a reasonable number of observations in each regime. For example, if we apply a trim of 15 %, this means that the middle 70% values of the sorted threshold variable are used as potential threshold values. Third, the TAR or MTAR model is estimated with each potential threshold value and the sum of squared residuals (SSR) for each trial is estimated. Finally, the threshold value resulting in the lowest SSR is considered a consistent estimate of the threshold τ.

According to the above specifications, we estimate four models: 1) TAR - Equ.5a with $(\tau) = 0$; 2) consistent TAR — Equ.5a with (τ) estimated; 3) MTAR — Equ.5b with $(\tau) = 0$; and 4) consistent MTAR — Equ.5b with (τ) estimated. we do not assume a particular specification for each price pair. Therefore, following Enders and Siklos (2001), we choose the appropriate adjustment mechanism for each price pair using the model selection criteria of AIC and BIC. Accordingly, the model with the lowest information criteria will be used for the respective price pair.

We obtain evidence on the asymmetric adjustments in the long-term relationship from two tests. First, we employ an F-test to examine the null hypothesis of no co-integration ($H_0 : \rho_1 = \rho_2 = 0$) against the alternative hypothesis of long-run relationship with either TAR or MTAR threshold adjustment. We use the critical values provided by Enders and Siklos (2001) because this test does not follow a standard distribution. Second, we examine the null hypothesis of the symmetric adjustment process toward the long-run equilibrium ($H_0 : \rho_1 = \rho_2$) using a standard F-test. If the null hypothesis is rejected, we conclude that there is an asymmetric adjustment process.

4.3. Asymmetric error correction model with threshold co-integration

The Error Correction Model (ECM) considers each variable as endogenous and consists of two elements: a linear combination of past values of all variables in the system; and an error correction term, which is the one period-lagged error of the long-run equilibrium relationship between each price pair. The ECM is described as follows:

$$\triangle Y_t = \lambda + \delta ECT_{t-1} + \sum_{l=1}^{k} \beta_k \triangle Y_{t-k} + \epsilon_t \tag{6}$$

where Y_t is a two-dimensional price vector containing the pairs of gas price series (i.e., (TTF, EAX); (HH, TTF); and (HH, EAX)). If there is any deviation from the equilibrium position, in the price differential of a natural gas pair, δ reveal the time taken (in days) for the equilibrium adjustment to occur.

If there is a threshold co-integration between the price series, the asymmetric Error Correction Model (ECM) can be estimated to analyze differential adjustments to positive and negative short-term deviations as follows (Enders and Granger, 1998; Enders and Siklos, 2001):

$$\triangle Y_t = \lambda + \delta^+ ECT^+_{t-1} + \delta^- ECT^-_{t-1} + \sum_{l=1}^{k} \beta_k \triangle Y_{t-k} + \epsilon_t \tag{7}$$

The error correction term in Equ.7 is constructed based on the threshold co-integration regressions in Equ.4, 5a, and 5b. Moreover, this error correction term definition considers the asymmetry of price response to deviations from long-term equilibrium and incorporates the impact of threshold co-integration through the Heaviside indicator in Equ.5a and 5b. For the TTF-EAX model, the high (low) regime is associated with the time period when positive (negative) divergences in the long-run equilibrium result from increases (decreases) in TTF or decreases (increases) in EAX. For the HH-TTF and HH-EAX models, the high regime corresponds to the time period when positive (negative) divergences in the long-run equilibrium result from increases (decreases) in HH or decreases (increases) in TTF and EAX.

4.4. Granger causality relationship

We use Granger causality tests to examine the lead-lag relationship in the global gas market. This allows us to infer whether one market helps forecast the pricing of the other. For example, suppose there is a uni-directional causality running from TTF to EAX. In that case, past values of TTF should contain information that helps predict EAX prices beyond the information contained in past values of EAX alone. In such a case, the lead-lag relationship between the two markets can be defined, leading to opportunities for abnormal returns in the global gas market.

To account for the dynamic behavior of this hypothesis, we employ the time-varying Granger causality test developed by Shi et al. (2020). This test allows us to determine if the causal relationships change over a specified time period by defining the starting and ending dates of any episodes of causality. Additionally, the test accommodates non-stationary variables in the Vector Auto-Regressive (VAR) model following the approach of Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996). To obtain a sequence of test statistics over time, we utilize the rolling window algorithm (Swanson, 1998). We also specify the model using heteroscedasticity-robust test statistics and calculate the critical values through bootstrapping procedures with 200 replications. For brevity, we move the detailed description of this test to Appendix .3.

4.5. Conducting the analysis over sub-samples

As mentioned above, the global natural gas market experienced two major shocks during the investigated period, namely the COVID-19 pandemic at the beginning of 2020 and geopolitical tensions at the end of 2021. These shocks are likely to have impacted the price transmission process, affecting the market fundamentals in each regional market, changing the transaction costs, and influencing market regulation in the respective regions. Not accounting for those breaks in the time series can lead to misleading results when analyzing the cointegration of the three regional gas markets over the period of 2016-2022. Additionally, the threshold cointegration approach utilized in this study is based on the premise of constant transaction costs throughout the analyzed period. However, this assumption may be overly restrictive in light of the current market dynamics. Moreover, market integration theory states that the existence of demand and supply shocks makes the validity of the integration process time-varying (Dukhanina and Massol, 2018; Spiller and Huang, 1986). Therefore, to explore how those shocks have affected the long-run relationship in the global gas market, we conduct our analysis over three subsamples: the pre-pandemic period (01/01/2016 - 20/03/2020), the pandemic peak period (23/03/2020 - 24/09/2021), and the global geopolitical tensions period (27/09/2021 - 31/10/2022). We also gain insight from the co-integration test of Maki (2012) over the entire period of 2016-2022, which suggests that these events have impacted the long-term relationship in the global gas market. For brevity, we move the results of this test to Appendix .2.

5. Stylized Facts

Our empirical analysis uses daily gas price series for the one-month ahead futures for the North American, European, and Asian gas markets. These prices are quoted for delivering a specified quantity of natural gas, with a delivery period of one month in the trading futures contract. The price data are collected for the respective trading hubs in the three regions: HH, TTF, and EAX[10] gas futures from 01/01/2016 to 31/10/2022. They are measured in USD per million British Thermal Unit (MMBtu).

Figure 1 presents the trend of the three gas price series from 2016 to 2022. The graphs demonstrate that the three gas prices exhibit a comparable pattern throughout the period under examination. It is clearly visible that there is a substantial decrease in prices in March 2020, likely caused by the outbreak of COVID-19 and its impact on natural gas demand. This was further exacerbated by historically mild temperatures.[11] Accordingly, the global natural gas market was oversupplied, which prompted the oil and gas industry to implement cost-saving measures and postpone investments to compensate for the substantial decline in revenue (IEA, 2020a). Figure 1 also shows that natural gas prices began to increase again in the second half of 2021. This can be attributed to the resurgence of demand from the industrial and heating sectors as economic activity rebounds and extreme weather events occur. It is also clear that while the

[10]The EAX price is an average of the front-month prices for the East Asian Countries, namely Japan, China, South Korea, and Taiwan. We refer the reader to this hyperlink for more information on this index: EAX index.

[11]For example, the decreased demand for heating in the residential and commercial sectors due to milder temperatures led to a drop of more than 3% year-over-year during the first quarter of 2020. This resulted from a decrease of over 5% in heating degree days across the main regions where gas is consumed (IEA, 2020e).

three price series follow a similar pattern of fluctuation, the HH series consistently remains lower than both the EAX and TTF indices throughout the entire period, with this gap becoming particularly pronounced towards the end of the period. This is because the European and Asian markets rely on international trade and the availability of flexible gas volumes (i.e., especially in Europe, due to the decreasing indigenous production). Additionally, the United States is a net exporter of natural gas, which contributes to the low price levels near the production costs. Despite this general trend, the data reveal that the HH price was relatively higher than the TTF and EAX prices between the end of April and mid-June 2020. This can be attributed to a confluence of factors, including the economic slowdown caused by the COVID-19 pandemic, an uptick in LNG deliveries to Europe and Asia, and high levels of European gas inventories (IEA, 2020d).

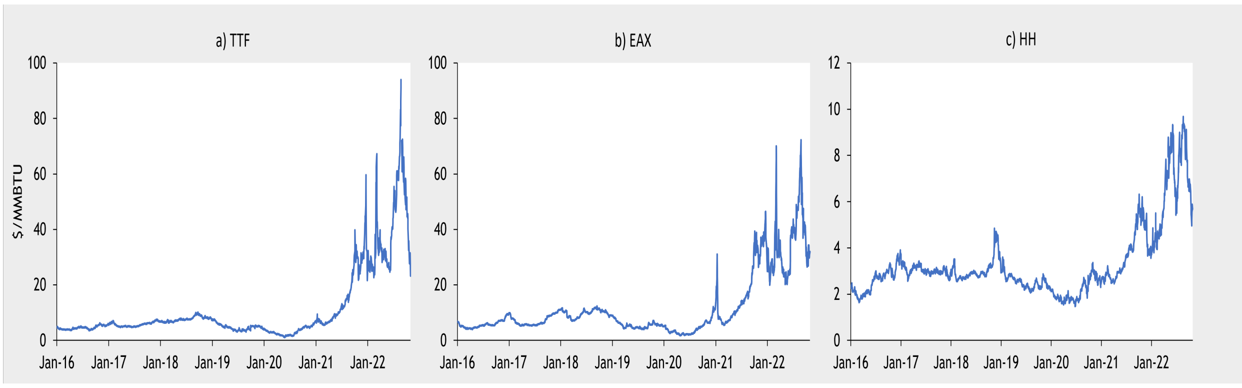

Figure (1) Daily natural gas prices from Jan-2016 to Oct-2022 (USD/MMBTU)
Source: Own construction

Table 1 provides summary statistics for the daily price series and gives initial insights into the overall behavior of the three gas prices over three distinct periods: pre-pandemic, pandemic peak, and global geopolitical tensions[12]. Three main insights stem from this table. Firstly, a comparison of the statistical measures of the three price series across the three periods shows a clear difference. Specifically, the mean, variance, and coefficient of variation (CV)[13] for TTF, EAX, and HH all exhibit a significant increase from pre-pandemic to pandemic peak and global tensions, with the most notable increases seen in the latter period. Secondly, the skewness of the gas prices has increased over time, indicating that the distribution of prices has become more asymmetrical. Specifically, there is an excess of high-priced observations in the global tensions period, which deviates from the symmetrical distribution of a normal distribution. Similarly, the kurtosis increased, indicating that the data had more extreme values than a normal distribution would have. This suggests that the gas prices were more volatile than expected. The Jarque-Bera test confirms

[12] Note that we use "global geopolitical tensions" or "global tensions" interchangeably.

[13] The coefficient of variation (CV) is a metric for comparing the relative variability of different data sets. It is obtained by dividing the standard deviation by the mean and multiplying the result by 100, which expresses the outcome as a percentage. In the context of Table 1, the CV for TTF, EAX, and HH reflects the degree of variation in gas prices across the three periods, with a higher CV indicating a greater level of volatility.

that the data does not conform to a normal distribution, which is consistent with these observations. Lastly, there are discernible distinctions between the TTF and EAX time series compared to the HH time series. The mean, variance, and CV for TTF and EAX are consistently higher than those for HH, and this trend is particularly pronounced in the post-GPT periods.

Table (1) Summary statistics

	Pre-pandemic			Pandemic peak			Global Geopolitical Tensions		
	TTF	EAX	HH	TTF	EAX	HH	TTF	EAX	HH
Mean	5.650	6.868	2.785	6.829	7.806	2.828	39.177	34.843	6.188
Variance	2.284	5.167	0.239	25.117	28.026	0.634	216.752	97.661	2.851
CV (%)	26.746	33.093	17.552	73.384	67.822	28.164	37.579	28.362	27.288
Skewness	0.577	0.699	0.340	1.552	1.340	0.842	1.301	1.151	0.291
Kurtosis	2.910	2.681	4.127	5.463	4.713	3.850	4.254	4.728	1.941
JB (test statistic)	61.550	94.300	79.517	259.079	166.866	58.696	96.955	96.279	16.958
JB (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of obs.	1101	1101	1101	396	396	396	279	279	279

Note: The data for this table was constructed by the authors. Note that CV stands for the coefficient of variation, which measures the relative variability of the natural gas price series. It is calculated as the ratio of the standard deviation to the mean, expressed as a percentage. Additionally, the Jarque-Bera (JB) test was used to determine if the data is normally distributed. The null hypothesis of the JB test is that the sample data is normally distributed.

6. Empirical Results

In this section, we analyze the impact of the pandemic and geopolitical tensions on market integration by conducting a comprehensive examination of three subperiods: pre-pandemic, pandemic peak, and global geopolitical tensions. The steps of our analysis include assessing the stationarity property of the three price series, examining linear and non-linear co-integration relationships, estimating error correction models, and evaluating the time-varying Granger causality hypothesis. Through this approach, we can gain a better understanding of the degree and dynamics of market integration before and after the identified shocks.

6.1. Unit root tests

A necessary condition for conducting cointegration analysis is the presence of a unit root, which indicates that the price series are integrated of order I (1). To ensure reliable outcomes, we conducted three unit root tests: the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS). The null hypothesis for ADF and PP states that the data series has a unit root, with the alternative being that it is stationary. Conversely, the null hypothesis for KPSS indicates that the variable is stationary.[14] Table 2 summarizes the results of the tests for the levels and first differences of the three price series in each sub-period. The results indicate that the three price series are not stationary in levels but are stationary in first differences at the 1% significance level. Thus, it is concluded that the three gas prices are I(1).

[14] We conduct these additional tests to confirm the univariate properties of the three price series. For a detailed review of the employed unit root tests, please see Maddala and Kim (1998).

Table (2) Time series properties of the data

		ADF		Philips Perron		KPSS	
	Period	Levels	First difference	Levels	First difference	Levels	First difference
EAX	Pre-pandemic	-0.8894	-14.160*	-0.906	-29.700*	2.139*	0.117
	Pandemic peak	-2.714	-11.721*	-2.492	-16.491*	0.426*	0.592
	Global tensions	-2.427	-11.360*	-2.811	-14.613*	0.329*	0.062
TTF	Pre-pandemic	-0.326	-24.090*	-0.0313	-34.215*	2.283*	0.137
	Pandemic peak	-2.222	-13.823*	-2.491	-19.304*	0.350*	1.303
	Global tensions	-2.949	-8.056*	-2.098	-15.359*	0.248*	0.094
HH	Pre-pandemic	-1.738	-19.167*	-1.957	-35.082*	1.728*	0.111
	Pandemic peak	-1.956	-14.749*	-1.954	-20.863*	0.479*	0.856
	Global tensions	-1.926	-12.142*	-1.801	-17.643*	0.414*	0.121

Notes: The lag selection for ADF and KPSS tests is based on Akaike Information Criteria (AIC). The test equations are estimated, including an intercept and trend for the variables in levels, whereas they include only an intercept for the first differences. * represents the 1% significance level. The three series are expressed in logarithms. The Critical values are obtained from MacKinnon (2010). For brevity, we move them to Table ?? in the Appendix. "Global tensions" stands for the global geopolitical tensions period.

6.2. Co-integration analysis

Since the time-series properties of the gas prices indicate that they are stationary in their first differences, a co-integration test can be applied to examine the long-run relationships between them. The analysis estimates both the linear and non-linear (threshold-based) co-integration relationships between pairs of the three gas prices.

In the context of linear co-integration, we use the two-step approach proposed by Engle and Granger (1987). This approach involves estimating the long-run relationship for each price pair in the first step, according to the specification in Equation 2. Then, we use the residuals obtained from this regression to perform a unit root test as specified in Equation 3. However, a significant challenge in the Engle-Granger method is the selection of dependent and independent variables for the regression, which can lead to inconsistent conclusions. To address this issue, we use the asymptotic test proposed by Phillips and Ouliaris (1990).[15] By combining the Engle-Granger approach with the Phillips-Ouliaris test, we obtain a more robust assessment of linear co-integration.

Table 3 presents the results of the two-step analysis. The first two columns report the estimated coefficients, while the last two columns provide the test statistics for the residuals' order of integration. Our results show that the TTF-EAX gas price series are linearly co-integrated over the three sub-periods, whereas the HH market is co-integrated with the other two markets only in the first two sub-periods, suggesting that the American market decoupled from the European and Asian markets in the global geopolitical tensions period. Additionally, our findings indicate a decrease in the cross-price elasticity coefficient (β_1) for the pandemic peak and global tensions periods, suggesting a reduction in the global gas

[15]This test comprises two residual-based tests: the variance ratio test (Z_t) and the multivariate trace statistics (Z_α). These tests are residual-based co-integration tests that use scalar unit root tests to compare a null hypothesis of no co-integration to the alternative of co-integration. The two tests are based on residuals of an AR(1) equation. However, Z_α has an advantage over Z_t in being invariant to normalization and providing consistent results regardless of the dependent variable choice.

market's degree of integration. Furthermore, the estimated β_1 coefficient for HH-TTF and HH-EAX is smaller than that of TTF-EAX, indicating that HH moves in the long run with TTF and EAX, but its levels might be significantly different in the short run due to structural differences in the North American market (i.e., it is a highly competitive market and oversupplied due to the shale gas revolution, resulting in lower price levels). Lastly, we observe that the constant coefficient (β_1) for the three price pairs varies among the three sub-samples, with an increasing value in the second and third sub-samples, implying a widening margin between the price pairs during those periods.

Table (3) Testing for linear cointegration

		OLS estimation results				Testing for linear co-integration	
	Period	β_0		β_1		ADF test	(Z_t, Z_α)
EAX - TTF	Pre-pandemic	-0.077	[0.021]	1.150	[0.012]	-6.078***	(-5.940, -68.260)***
	Pandemic peak	0.292	[0.017]	0.923	[0.009]	-5.137***	(-4.919, -45.596)***
	Global tensions	1.137	[0.098]	0.659	[0.027]	-4.963***	(-5.054, -48.366)***
HH - TTF	Pre-pandemic	0.210	[0.025]	0.471	[0.014]	-3.330**	(-3.697, -26.893)**
	Pandemic peak	0.402	[0.014]	0.357	[0.008]	-3.352**	(-3.656, -24.004)**
	Global tensions	0.425	[0.160]	0.377	[0.044]	-1.923	(-1.965, -07.729)
HH - EAX	Pre-pandemic	0.299	[0.023]	0.379	[0.012]	-3.238**	(-3.482, -23.995)**
	Pandemic peak	0.310	[0.016]	0.376	[0.008]	-3.487**	(-3.605, -22.948)**
	Global tensions	0.961	[0.214]	0.234	[0.061]	-1.532	(-1.635, -05.323)

Note: Standard errors of the estimated coefficients are given in the squared brackets. The CV for Zt/Za of the Phillips and Ouliaris (1990) are: CV(1%):-3.962/-28.322; CV(5%): -3.365/-20.494; CV(10%):-3.066/-17.039. The critical values for the ADF test are: CV(1%):-3.936;CV(5%):-3.358;CV(10%):-3.060. Critical values of both tests are obtained from MacKinnon (2010). A rejection of the null hypothesis of a unit root at the 1 and 5 percent significance level is denoted by *** and ** and, respectively. "Global tensions" stands for the global geopolitical tensions period.

The Engle-Granger approach assumes symmetric price transmission between markets, meaning that it is independent of the magnitude of the deviation from the long-run equilibrium. Therefore, this approach is misspecified when the adjustment process to the equilibrium level is non-linear. To account for this asymmetry, we conduct a threshold co-integration analysis using the consistent TAR and M-TAR models (Enders and Siklos, 2001), as explained in section 4. We estimate the TAR and M-TAR models and their consistent counterparts for each price pair over the three sub-periods. Then, we choose between the models using model selection tests proposed by Enders and Siklos (2001). Our analysis shows that the consistent M-TAR model is optimal for modeling the adjustment mechanism of EAX-TTF and HH-EAX, while the consistent TAR model is optimal for HH-TTF. Detailed results of these selection criteria are presented in the Appendix.

Table 4 provides the results of the threshold co-integration test. Based on the information criteria, our analysis suggests that the appropriate adjustment mechanism for the EAX-TTF and HH-EAX price pair is the M-TAR model. In contrast, the appropriate mechanism for the HH-TTF pair is the TAR model. Column (1) presents the estimated threshold values, which reflect the change in the spread required to adjust asymmetrically back to the long-run position. We find that these threshold estimates also differ across the sub-periods considered in our analysis. This finding suggests that the transaction costs in the global gas market have been affected by the uncertainty and risk associated with the two investigated shocks, leading to changing threshold values. Therefore, analyzing the sub-periods helps us account for these changes in transaction costs and their effect on the price transmission process. Columns (2) and (3) show the estimated parameters of ρ_1 and ρ_2 as specified in equation 4. Note that ρ_1 represents positive deviations from long-run equilibrium, whereas ρ_2 reflects the negative deviations. If the absolute value of ρ_1 is greater (smaller) than that of ρ_2, this reveals that faster convergence occurs with positive (negative) deviations from the long-run equilibrium. For example, the results for the TTF-EAX price pair in the pre-pandemic period show that $|\rho_1| > |\rho_2|$, suggesting that positive deviations from the long-run (i.e., resulting from increases in TTF or decreases in EAX) would be eliminated faster than the negative deviations (i.e., resulting from increases in EAX or decreases in TTF).[16] Column (4) gives the first F-statistic for the null hypothesis ($H_0 : \rho_1 = \rho_2 = 0$) against the alternative of cointegration with either TAR or M-TAR threshold adjustment. The estimated results indicate that the test statistics exceed the corresponding critical values for the EAX-TTF price pair in all three sub-periods and for the HH-EAX and HH-TTF pairs in the first two periods. Column (5) reports the results of testing the null hypothesis of symmetric adjustment ($H_0 : \rho_1 = \rho_2$). The results suggest that the adjustment process in the global gas market is asymmetric, and, accordingly, traders respond differently depending on the direction the spread is moving from its long-run equilibrium.

Overall, the results indicate non-linear co-integration between the EAX-TTF price pair in all three periods, meaning that the adjustment process to the long-run equilibrium depends on whether the spread is widening or narrowing. Specifically, we consistently observe that $|\rho_2|$ is greater than $|\rho_1|$, which suggests that negative deviations from the long-run equilibrium (i.e., resulting from increases in TTF or decreases in EAX) are corrected faster than positive deviations (i.e., resulting from increases in EAX or decreases in TTF). Consequently, there is substantially faster convergence for deviations below the threshold than for deviations above the threshold. One possible explanation for this asymmetry is the existence of financial market frictions, transaction costs, and institutional and regulatory limitations, which could lead to faster convergence to the long-term equilibrium for negative deviations. However, the findings for the HH-TTF and HH-EAX price pairs differ. Although both pairs exhibit non-linear co-integration in the pre-pandemic and pandemic peak periods, there is no evidence of non-linear co-integration in the global tensions period. These results suggest that supply shocks associated with geopolitical tensions in the European market have resulted in a persistent price differential between HH and the other two markets. This differential is lower than the transaction costs between them, indicating a lack of non-linear co-integration.

[16] Note that this interpretation is only applicable if the two null hypotheses of $\Phi(H_0 : \rho_1 = \rho_2 = 0)$ and $F(H_0 : \rho_1 = \rho_2 = 0)$ are rejected. Hence, this does not hold for the relationship between HH and EAX in the last sub-sample (Global tensions).

Table (4) Results of threshold co-integration analysis

		(1) Threshold	(2) ρ_1	(3) ρ_2	(4) $\Phi(H_0 : \rho_1 = \rho_2 = 0)$	(5) $F(H_0 : \rho_1 = \rho_2 = 0)$
EAX – TTF	Pre-pandemic	-0.028	-0.050	-0.113	18.707***	5.764**
			[0.012]	[0.024]		(0.017)
	Pandemic peak	0.014	-0.060	-0.173	14.530***	5.779**
			[0.036]	[0.033]		(0.017)
	Global tensions	0.112	0.188	-0.193	15.684***	6.166**
			[0.152]	[0.036]		(0.014)
HH – TTF	Pre-pandemic	-0.122	-0.009	-0.045	7.231**	5.989**
			[0.007]	[0.012]		(0.015)
	Pandemic peak	-0.115	-0.033	-0.122	8.570***	5.740**
			[0.020]	[0.032]		(0.017)
	Global tensions	0.394	-0.042	-0.022	2.050	0.374
			[0.027]	[0.017]		(0.541)
HH – EAX	Pre-pandemic	-0.024	-0.023	0.007	5.785*	3.145*
			[0.007]	[0.016]		(0.076)
	Pandemic peak	0.022	-0.130	-0.035	9.245***	6.164**
			[0.034]	[0.018]		(0.013)
	Global tensions	0.079	0.063	-0.023	2.453	2.397
			[0.054]	[0.012]		(0.123)

Note: Column (1) provides the estimated threshold values, reflecting the required change in the spread to adjust asymmetrically to the long-run equilibrium. Columns (2) and (3) provide the estimated coefficients ρ_1 and ρ_2 in Equ. (3). Column (4) shows the null hypothesis $\Phi(H_0 : \rho_1 = \rho_2 = 0)$ tests for null hypothesis of no co-integration with the critical values from Enders and Siklos (2001) as follows: C.V(1%) is 8.310; C.V(5%) is 6.050; C.V(10%) is 5.060. Column (5) gives the second null hypothesis $F(H_0 : \rho_1 = \rho_2 = 0)$, which examines the asymmetry of the price transmission process with a standard F-test. ***, **, and * denote significance at the 1%, 5%, and 10% levels. Based on Information Criteria, the asymmetric price transmission for the EAX-TTF and HH-EAX are estimated using the M-TAR model, whereas the TAR model is used for the HH-TTF. The details on the selection criteria are available in Table ??. "Global tensions" stands for the global geopolitical tensions period.

6.3. *Results of the (a)symmetric error correction model*

In this step, we estimate the symmetric and asymmetric error correction models (ECMs) to examine the adjustments of individual prices to the long-run equilibrium. We estimate the symmetric (asymmetric) ECM for each price pair if the corresponding co-integration results from the previous step show symmetric (asymmetric) adjustments to the long-run equilibrium in the corresponding sub-period. It is important to note that price transmission between EAX and TTF can occur through physical trade facilitated by a third party or a swing supplier[17], whereas the transmission between HH and the other two prices can happen through direct physical trade from the American to the European and Asian markets.

Table 5 presents the estimation results of the ECM for the three sub-samples.[18] Two general points are noted from these results. First, based on our specification, the signs (-) and (+) are expected for the adjustment coefficients of the ECT of P_t^A and P_t^B, respectively, meaning that both prices contribute to the error correction mechanism. Second, the magnitude of the ECT is interpreted in terms of how many days

[17] A swing supplier, such as Qatar, is flexible to unexpected shocks in the market fundamentals in both European and Asian gas markets and can change their production/exports plans to meet the changes in those markets (Kim et al., 2020).

[18] The results of the diagnostic checks for each estimated ECM (such as the serial correlation and normality tests) indicate that the estimated models perform reasonably well. For brevity, we do not report the diagnostic checks here. However, they are available upon request from the corresponding author.

are required for the deviations from the equilibrium to be corrected. For example, if the ECT is 0.250, then this implies that the respective price responds in the short-term to the deviations by about 25% per day (i.e., it takes four days to be eliminated).

Table (5) Results of symmetric and asymmetric VECM

		Regime	EAX	TTF	HH	TTF	HH	EAX
Pre-pandemic	Symmetric		-0.034***	0.024***	-0.015**	0.008	-0.014**	0.011*
			(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
	Asymmetric	High regime	-0.029***	0.020**	-0.009	0.010	-0.018**	0.012**
			(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)
		Low regime	-0.055***	0.042***	-0.035***	0.004	0.008	0.003
			(0.015)	(0.016)	(0.013)	(0.013)	(0.015)	(0.014)
Pandemic peak	Symmetric		-0.086***	0.039**	-0.043***	0.026	-0.032***	0.062**
			(0.019)	(0.018)	(0.015)	(0.022)	(0.015)	(0.023)
	Asymmetric	High regime	-0.040*	0.031	-0.036**	0.022	-0.094**	0.112**
			(0.027)	(0.026)	(0.017)	(0.024)	(0.032)	(0.049)
		Low regime	-0.125***	0.046*	-0.080**	0.065	-0.018	0.036
			(0.025)	(0.024)	(0.033)	(0.048)	(0.017)	(0.026)
Global tensions	Symmetric		-0.107***	0.031				
			(0.030)	(0.039)				
	Asymmetric	High regime	0.205	0.188				
			(0.130)	(0.168)				
		Low regime	-0.119***	0.025				
			(0.031)	(0.039)				

Note: The high and low regimes are divided by the sign of ECT (i.e., whether the differential between the two prices multiplied by the co-integrating vector is greater or less than the threshold). The asterisks *,**, and *** attached to the significance levels at the 10%, 5% or 1%, respectively. The number of lags are defined based on the VAR model selection criteria. The number of lags for models estimated for the periods (2016-2021) and (2016-2019) is 3, whereas the number of lags for the models estimate of the period (2020-2021) is 1. The autoregressive coefficients are not reported to conserve space. "Global tensions" stands for the global geopolitical tensions period.

Regarding the price transmission between EAX and TTF, our results indicate that in the first sub-sample, both prices have a significant effect on the correction towards the long-run equilibrium in both high and low regimes. This highlights the active role of both gas prices in responding to deviations from the long-run equilibrium in the short run, albeit at different adjustment speeds. Specifically, the correction speed of the two prices is higher in the low regime, implying that discrepancies caused by rising TTF or falling EAX are eliminated quickly, whereas other discrepancies persist. In the second sub-sample, the EAX price continued to have a significant impact on the correction towards the long-run equilibrium in both regimes, while the TTF price was only significant in the low regime. This suggests that the EAX price played a more dominant role in driving the correction towards the long-run equilibrium, while TTF only responded to negative deviations. In the third sub-sample, the EAX price's impact on the correction towards the long-run equilibrium was limited to the low regime, implying that TTF was leading the market during this period. Moreover, we observe that the magnitudes of the error correction terms of the two prices were relatively higher in the pandemic peak and global tensions sub-samples, implying that the gas prices adjusted more quickly to deviations from the long-run equilibrium during these periods. This is likely because gas prices were high enough to cover the increased transaction costs of arbitraging natural gas between TTF and EAX, or that information transmission among traders and suppliers was quick enough, leading to closer integration of the markets during times of crisis (i.e., contagion effect (Eichengreen et al., 1996)).

The estimated results of the adjustment process between the pairs of HH-TTF and HH-EAX are presented in Columns 3 to 6 of Table 5. The ECM is not estimated for the global tensions sub-period as there is no evidence of co-integration between HH and the other two markets. The results of the ECM analysis for the price transmission between HH and TTF showed that, in the first sub-sample, HH adjusted to divergences from the long-run equilibrium in the low regime (where TTF was relatively higher than HH), while in the pandemic peak sub-sample, HH had a significant ECT in both high and low regimes, with a higher magnitude in the latter. Meanwhile, the ECT of TTF was insignificant in both regimes. In the case of the price transmission between HH and EAX, the results showed that, in the pre-pandemic sub-sample, both HH and EAX had a significant ECT only in the high regime. In the pandemic peak sub-sample, the ECT of HH and EAX remained significant only in the high regime. These findings suggest that the price transmission process between HH and TTF differed from that between HH and EAX, with HH playing a dominant role in correcting towards the long-run equilibrium in the case of HH-TTF, while both HH and EAX actively participated in the correction toward the long-run relationship.

6.4. Time varying Granger Causality test

We examine the Granger causality relationship based on Fama (1970)'s simultaneous information processing hypothesis (i.e., the price discovery process in the global gas market). The Granger causality hypothesis is used here to infer whether one regional market helps forecast the pricing of the other region. For instance, if TTF is found to Granger cause EAX, then past values of TTF hold additional information that helps in predicting EAX prices, beyond the information that is contained in past values of EAX. This implies the presence of instant information spillovers from TTF to EAX.

Figure 2 displays the sequence of test statistics from the rolling window algorithm along with the bootstrapped critical values of 10% and 5%.[19] A significant causality relationship is found when the estimated Wald test statistic exceeds the critical values during a particular period. Our findings reveal that EAX exerts a Granger causal influence on TTF and HH at the end of 2017 and certain dates in 2020 and 2021, which align with different shocks in the Asian gas market, such as the gas supply shortage at the end of 2017 and the reduction of gas demand due to lockdown measures in 2020. Additionally, our analysis reveals that TTF has a significant causal influence on both HH and EAX during two specific time periods. The first instance occurs in the first quarter of 2020 and is associated with the demand shocks that took place in the European gas market due to the pandemic. The second instance is observed in the last quarter of 2021, until the end of our sample. This is attributed to the supply shocks that impacted the European

[19] As the three gas price series are integrated of order one, we conduct the estimation of time-varying causality through a Vector Autoregression (VAR) model augmented with one lag.

gas market during this period. Lastly, we note significant causality from HH to TTF and EAX, which occurred mainly during 2018 and 2019, coinciding with the availability of cheap and abundant natural gas resources in the North American market. Overall, our results demonstrate that the Granger causality relationship among the three regional gas markets is dynamic, meaning that the information spillover among these regions changes over time, indicating evolving market linkages in the global gas market.

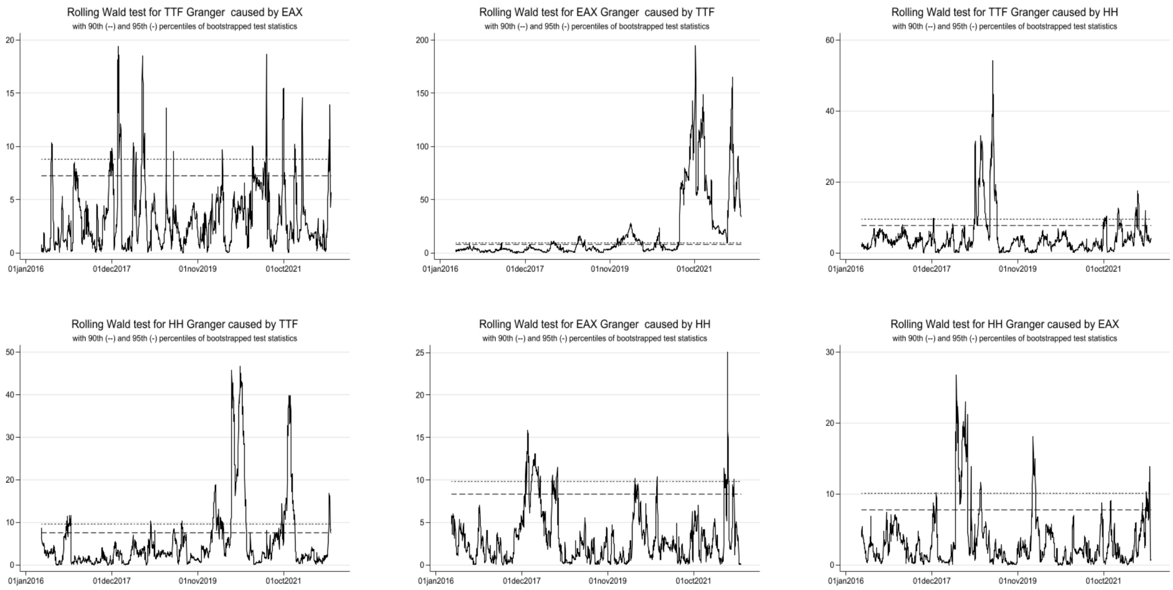

Figure (2) Time-varying Granger causality with heteroskedastic-robust specification

7. Discussion

This section provides an overview of the econometric analysis results obtained in the previous section. Then, we investigate which changes in the global natural gas market are consistent with these empirical findings

7.1. An Overview of our Empirical Findings

As previously mentioned, the market integration hypothesis refers to the degree to which a price shock in one regional market affects other regions. In this study, we use linear co-integration, threshold co-integration, and asymmetric error correction models to analyze price dynamics in the global natural gas market and assess asymmetric price transmission. Evidence of a co-integration relationship suggests a long-term link between markets that constrains the divergence of price series. However, the COVID-19 pandemic in early 2020 and geopolitical tensions at the end of 2021 may have disrupted the integration process among the three regional natural gas markets. Therefore, we examine how these external shocks affected the long-run relationship in the global gas market by dividing our analysis into three sub-samples: the pre-pandemic period, the pandemic peak period, and the global geopolitical period. We summarize the empirical results from the previous section and explain the connection between the results and events in the global gas market for each sub-period. Our goal is to provide insight into the importance of understanding market integration dynamics and their response to external shocks.

Overall, the results suggest that the degree and nature of price convergence vary across sub-periods and market pairs, indicating that external shocks affect the integration process among the three regional gas markets. Firstly, the Asian and European gas prices were found to be co-integrated in all three sub-periods, while HH is co-integrated with those two markets only in the first and second sub-periods. Secondly, the degree of integration between each price pair has decreased, particularly in the third sub-sample, suggesting that the convergence in the global gas market has declined due to recent demand and supply shocks. Thirdly, price differentials of the three price pairs adjust asymmetrically following a shock, indicating that they respond differently to positive shocks and negative deviations. Three possible reasons exist behind the asymmetric price transmission process in the international natural gas market. First, the interaction between heterogeneous market participants' expectations and risk aversion speculations can lead to asymmetric price transmissions among the three regions (i.e., based on the magnitude of deviations from the long-run equilibrium). Second, noise traders - those who make decisions based on false perceptions and analysis of the market circumstances - can push the price in one regional market up (or down), leading to increasing (or decreasing) price differentials until informed traders engage in this process and restore the equilibrium relationship.[20] Third, futures contract availability and market frictions might also result in an asymmetric price transmission with two regimes (Hammoudeh et al., 2008; Ihle and von Cramon-Taubadel, 2008). Fourthly, the Granger causality hypothesis analysis of information processing for price discovery between the three gas markets, depicted in Figure 2, suggests that this causality relationship changes over time and exhibits a dynamic behavior. In a relaxed market situation with abundant supply, the HH price provides price signals for forecasting prices in other markets, while in case of supply shortages and tight market conditions, the TTF becomes the leading reference point for price discovery. Lastly, the East Asian markets could always gain short-term influence through unexpected events and demand shocks.

7.2. Market conditions and shocks affecting the integration process

Building on our empirical findings, this section provides a qualitative analysis that examines the events and facts that have occurred in the global gas market across the three sub-periods we investigated, resulting in varying degrees of market integration.

[20] For example, the European Securities and Markets Authority (ESMA) has recently suggested allowing pauses in natural gas trading to give more time to market participants to process the flow of information and avoid noisy trading activities(ESMA, 2022).

7.2.1. Sub-period 1: Global gas markets on a growth path - Emergence of the U.S. as a global LNG exporter

The first sub-period of our analysis spans from the beginning of 2016 to March 2020 and featured relatively stable global gas market conditions. During this period, global natural gas demand significantly increased by 10%, or 354 billion cubic meters (bcm), primarily driven by Asia (+129 bcm or +17%) and North America (+116 bcm or +12%), compared to the previous growth of 4% between 2012 and 2016. This growth was mainly fueled by economic growth and coal-to-gas switching policies, such as China's coal-to-gas conversion program in 2017. As natural gas is produced and consumed in different regions, the global gas trade had to increase to meet the rising demand. As shown in Figure 3, global LNG exports increased from 358 bcm in 2016 to 480 bcm in 2019, with an average annual increase of 9%. The US played a significant role in this growth, accounting for an average annual share of 35% (Rystad Energy, 2023).

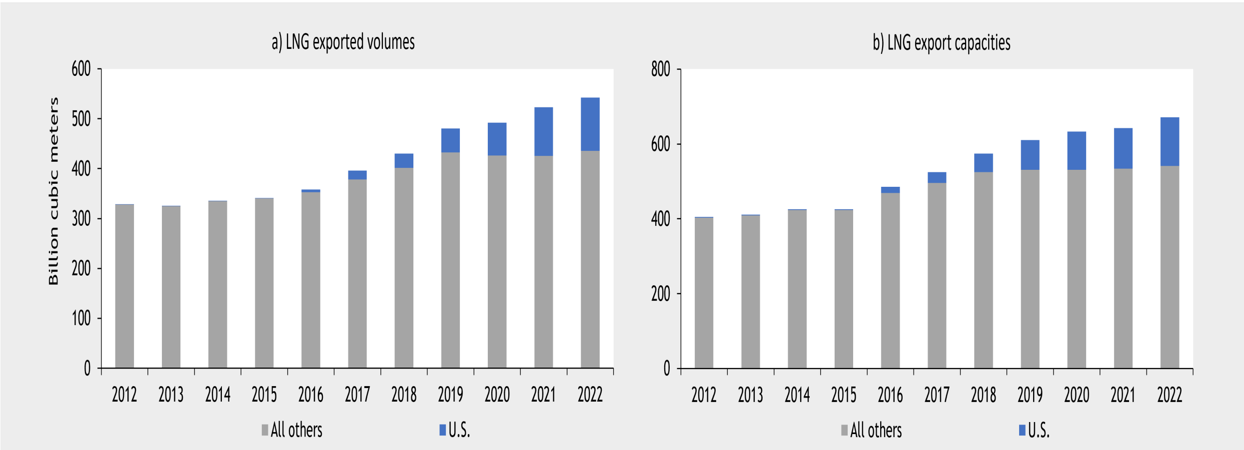

Figure (3) Annual global and U.S. LNG export volumes and capacities from 2012 to 2022 (Billion cubic meters) Source: Own construction based on Rystad Energy (2023).

Several factors supported this growing trend in the LNG market during this period. First, as depicted in Figure 3, the US started exporting LNG in 2016 and has since become a significant player in the global market, with a growing export volume every year. In contrast, other exporters have seen only a small rise in their export volumes throughout the years. Moreover, the US has continuously expanded its export capacity since 2016, with a steep rise in 2019, accounting for 52% of the global liquefaction capacity growth between 2016 and 2019.[21] Also, the global fleet for LNG cargoes grew by an average of 9% annually over this sub-sample (Rystad Energy, 2023). Second, the market witnessed structural changes in the contractual agreements. The share of total contracts with fixed destination clauses declined from 67% in 2016 to 24% in 2019, and new flexible destination volumes were introduced in the market (IEA, 2020c). Further, the

[21] Figure 3 shows that the total US export capacity increased from 16 bcm in 2016 to 95 bcm in 2019, accounting for about 500% increase over this period (EIA, 2023). This led to increasing LNG exports from 5 bcm in 2016 to 48 bcm in 2019 (Rystad Energy, 2023).

US LNG contracts provided more flexibility to the LNG market in two ways. On the one hand, they had no restrictions in the form of destination clauses. On the other hand, if the buyer did not take the contracted amount, the penalty was limited to the tolling or liquefaction fee instead of the full take-or-pay (ToP) penalty imposed by traditional contracts (IEA, 2020b). Third, relatively low charter rates were also responsible for the growth in the LNG market. Fourth, the LNG market witnessed an increase in spot and short-term transactions [22] during this period, leading to high market liquidity and lower transaction costs. For example, the share of spot and short-term volumes increased from 28% in 2016 to 34% in 2019 (GIILNG, 2017, 2020). The main reason for this increase is the growing LNG volume being handled by traders who can efficiently manage their portfolios by buying and selling LNG on different contract durations (GIILNG, 2019).

The aforementioned factors contributed to greater market integration in the global gas market by increasing market liquidity, reducing transaction costs, and facilitating inter-regional arbitrage. The growth of the global fleet of LNG carriers, the expansion of the U.S. LNG infrastructure, and the increasing flexibility of LNG contracts all played a significant role in this development.

7.2.2. The onset of the COVID-19 pandemic has triggered a downturn in global gas demand

The COVID-19 pandemic significantly impacted the global gas market, causing a demand shock. Global natural gas demand fell by over 82 bcm or more than 2% year-on-year in 2020, in contrast to the more than 2% annual growth observed in the past decade. The European, North American, and Asian markets experienced negative year-on-year growth of 3.5%, 2%, and 0.5%, respectively (Rystad Energy, 2023). The decline in demand was due to lockdown measures affecting economic activities, mild temperatures in the northern hemisphere during the winter of 2019-2020, and increased power generation from wind in Europe (IEA, 2020a).

As a result, storage levels reached record highs in underground storage facilities and LNG storage reservoirs, particularly in Europe and Asia.

For instance, Figure 4 shows that in Europe, the average storage level at the end of the withdrawal period in April 2020 was 25% (+28 bcm) above the average of the last five years (GIE, 2022). In Asia, stored LNG volumes were in June 2020 over 25% (+2 bcm) higher than the five-year average in 2020.

This subsequently led to a discontinuation of the long-lasting growth rate of LNG imports in Europe. As a result, there was a lower competition between Europe and Asia in the global market. The natural gas market also faced uncertainties and bottlenecks that affected the transaction costs of trading natural gas. First, oil and gas companies cut back or postponed investments in gas infrastructure projects due to the collapse of gas prices in regional markets caused by the pandemic (IEA, 2020a). Second, there were

[22] Spot and short-term contracts refer to trading LNG over one year but less than four years (IGU, 2021).

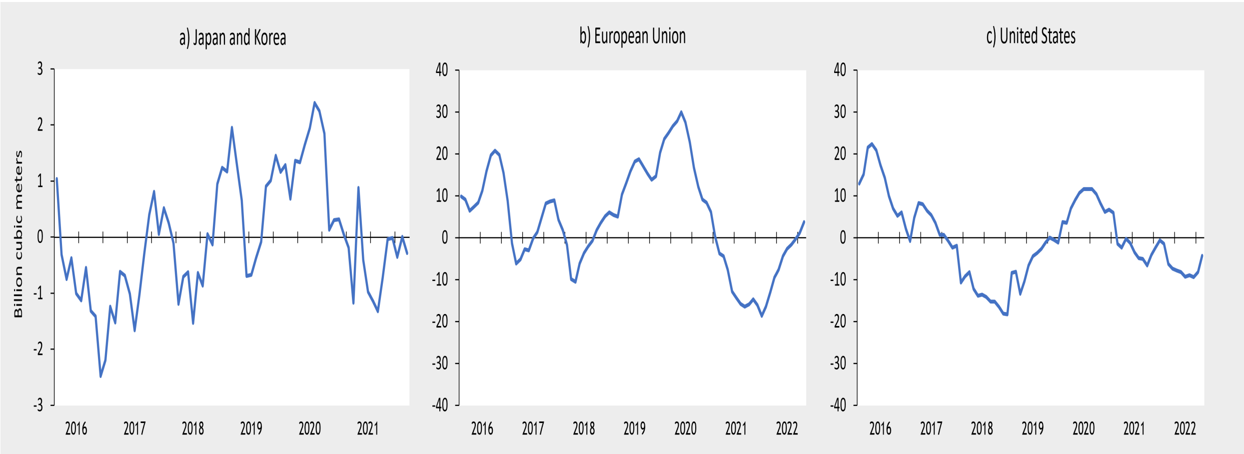

Figure (4) Difference between current storage inventories and the average inventories of the past 5 years (Billion cubic meters)
Source: Own construction based on (EIA, 2023; GIE, 2022; IEA, 2022)

supply restrictions of Norwegian gas to Europe due to maintenance work on pipelines in Norway in the first half of 2021 (ECB, 2022). Meanwhile, there was a decrease in European gas imports from Russia, with a drop of -36 bcm (-11%) in 2020 (Fulwood et al., 2022). Third, charter rates increased on average by about 23% compared to the first sub-period. The increased transaction costs, due to the increased transport and non-transport cost, were reflected in our empirical analysis through the threshold estimates (see Table 4).

Overall, the COVID-19 pandemic and its associated demand shock and increased storage levels in Europe and Asia led to reduced LNG imports, especially in Europe, while supply restrictions and bottlenecks also affected the transaction costs of trading natural gas. This resulted in lower market integration during this sub-period.

7.2.3. Geopolitical tensions in Europe affecting global natural gas supply

After COVID-19 restrictions were eased or lifted in many countries around the world, global gas demand increased by nearly 200 bcm (+5%) from 2020 to 2021, mainly due to the recovery of economic activities. On a continental basis, gas demand increased the most in Asia at 61 bcm (+7%), followed by Europe at 18 bcm (+3%) and North America at 13 bcm (+1%) (Rystad Energy, 2023). This was followed by the start of a gas price rally in the summer of 2021 on the gas market, driven by the uncertain supply situation associated with the loss of Russia as the largest gas supplier to the European gas market (ECB, 2022).

On the supply side, since September 2021, Russia has reduced daily gas flows[23] to Europe to the level of nominations from long-term contracts, resulting in no additional gas volumes being made available to the European spot market (Fulwood et al., 2022). This is clearly shown in Figure 5.a, which depicts the changes

[23]Russia has continuously curtailed its gas exports via the four main pipeline corridors: Nord Stream, Yamal, the Ukrainian route, and Turk Stream.

in Russian gas exports. For example, Russian pipeline natural gas exports to Europe decreased from 11.8 bcm in October 2020 to 9.1 bcm and 2 bcm in October 2021 and 2022, leading to year-on-year changes of about 25% and 80%, respectively (ENTSOG, 2022). This supply shock has caused gas prices in Europe and Asia to climb to new temporary record levels since September 2021. As a result, many European countries have started seeking ways to enhance the security and diversification of their energy supply from the global LNG market. Additionally, in the first half of 2022, many Western oil and gas companies announced the discontinuation of cooperation and investment in Russian stakes and assets (Refinitiv, 2022).

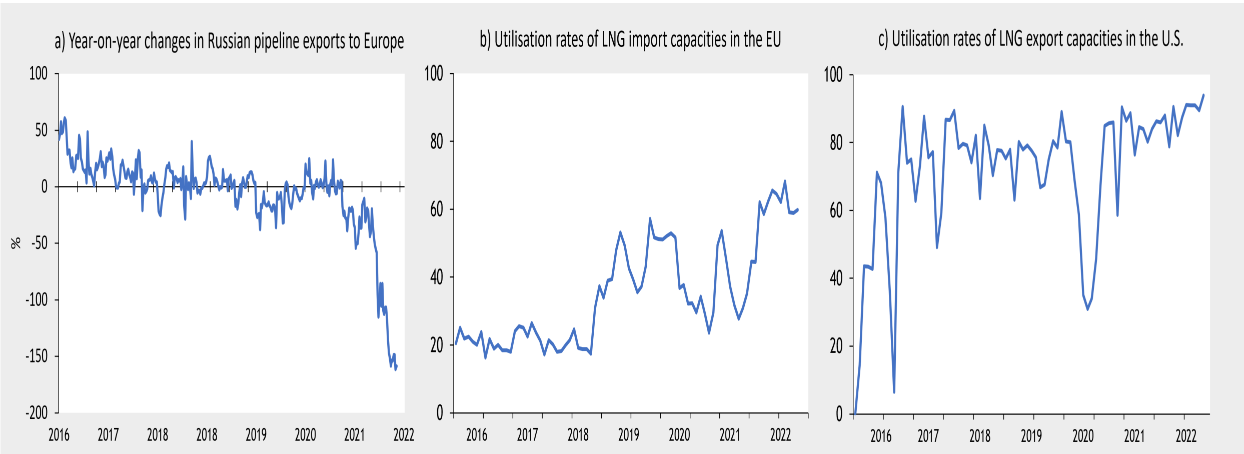

Figure (5) Changes in Russian pipeline exports to Europe and utilization rates of LNG infrastructure (%)
Source: Own construction based on (ENTSOG, 2022; GIE, 2022; EIA, 2023)

The supply-side distortions in the European gas market also had an impact on the levels of gas storage facilities. With the start of the injection period after the winter of 2020-2021, gas storage faced significant challenges as gas imports from Russia, which are crucial for gas storage injection, were increasingly reduced. Poor injection rates during the summer of 2021 resulted in average storage levels in the EU at the beginning of winter 2021-2022 of a maximum of 77%. Compared to previous years in Figure 4, this is an all-time low (GIE, 2022). At the end of winter 2021-2022, gas storage facilities in the EU were about 25% full on average. The concern about insufficient storage reserves during the winter, which could lead to a gas shortage, led the EU Council to introduce a regulation in June 2022 requiring all EU member states to fill their gas storage facilities to at least 80% by November 1, 2022, to prevent a critical situation like last winter's from occurring again [24]. On the demand side, gas demand in Europe responded to gas prices starting in July 2021. Within the European Union alone, gas demand dropped by 14% from 2021 to 2022 (-54 bcm) (of the European Union, 2023). In order to maintain a sufficient gas supply in Europe, efforts were focused on utilizing all other import corridors. Pipeline imports from the remaining pipeline corridors had already been

[24] https://www.consilium.europa.eu/en/press/press-releases/2022/06/27/council-adopts-regulation-gas-storage/

increased to nominal capacity at the end of 2021, so any further shortage of gas exports from Russia could not be compensated for with additional pipeline gas from Norway, North Africa, or Azerbaijan (Fulwood et al., 2022).

The aforementioned shocks on the supply side have significantly impacted the global LNG market. European LNG imports increased by 67% YoY in 2022, amounting to an additional 65 bcm (Rystad Energy, 2023). As a result, LNG import capacities in many regions of the continent were fully utilized as of December 2021 (Fulwood et al., 2022), as shown in Figure 5. Europe's importance in the global LNG trade consequently increased significantly within a year, with a significant share of the increased imports originating from the U.S. Between 2019 and 2021, the EU's share of total LNG exports from the US averaged 37%, but in 2022, nearly 70% of total U.S. LNG exports were sent to Europe, making it the top market for U.S. LNG. In the meantime, the U.S. LNG liquefaction plants in this sub-period were almost fully utilized, averaging nearly 90%, as depicted in Figure 5. However, the global LNG market faced further tightening of supply due to a fire in June 2022, causing the outage of the Freeport LNG terminal, which offers 20 bcm of annual liquefaction capacity (IEA, 2023). Furthermore, charter rates for the transport of LNG continued to rise, with rates for the Atlantic prompt and Pacific prompt increasing by 26% and 37%, respectively, compared to the second sub-period, contributing to rising transaction costs. Furthermore, we observe that China experienced a drop in LNG imports due to COVID-related disruptions, as depicted in Figure 6. This decreased demand for LNG from the Asian market may explain the relatively low degree of integration, especially during the third sub-sample.

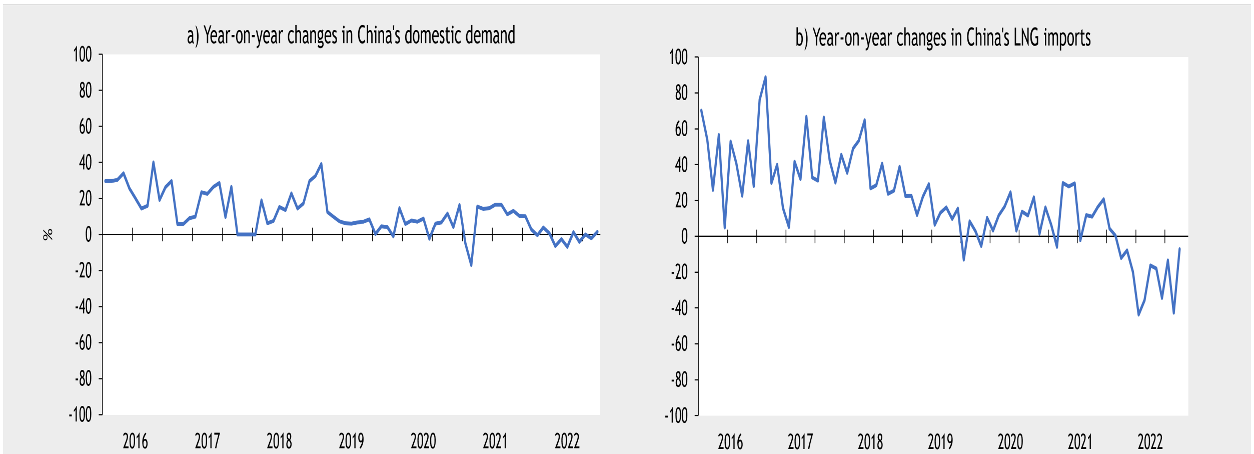

Figure (6) Changes in China's natural gas domestic demand and LNG imports(Year-on-Year Changes %)
Source: Own construction based on (GIE, 2022; EIA, 2023)

In summary, the global geopolitical tensions period was characterized by greater uncertainties in the global gas market, triggered by the supply shock in the European gas market. This was also reflected in market integration and transaction costs. Our results confirm that, in addition to increased transaction costs, market integration between the U.S. and the other two markets no longer exists. While market participants in Europe fully utilized the global LNG spot market, the U.S. tried to export more LNG to Europe, even though capacity limits had been reached. This may explain the decoupling of the European and American markets. Additionally, due to the high capacity utilization of LNG import terminals in Europe and decreased demand for LNG from China, the degree of integration between European and Asian gas markets declined during this period.

8. Conclusion

This study aims to investigate the long-term relationship between TTF, HH, and EAX, which are price benchmarks for Europe, the US, and Asia, respectively, between January 2016 and October 2022. Our analysis is divided into three periods: pre-pandemic, pandemic peak (due to the associated demand shock), and global geopolitical tensions (due to the corresponding supply shock). Using different techniques such as linear and threshold co-integration approaches, an asymmetric error correction model, and a time-varying Granger causality test, we examine the extent of the shocks' effects on market integration among the three benchmarks, establish whether the adjustment process is asymmetric, and test whether the Granger causality relationship in the global gas market is dynamic. Additionally, we investigate various gas market fundamentals and conditions that we believe are aligned with our empirical results from these approaches.

Our analysis shows that the extent and nature of price convergence vary across sub-periods and market pairs. This implies that the integration process among the three regional gas markets is affected by external shocks. Our results are summarized as follows. First, the Asian and European gas prices are found to be co-integrated in the three sub-periods, whereas the HH is co-integrated with those two markets only in the first and second sub-periods. A possible explanation for the decoupling in the third sub-sample is the congested LNG infrastructure in the US market. Second, our results reveal that the degree of integration between each price pair has decreased, particularly in the third sub-sample. This might indicate that the convergence in the global gas market has declined due to the associated demand and supply shocks. Third, we find that gas price differentials adjust asymmetrically following a shock, suggesting that they respond differently to positive shocks and negative deviations from a certain threshold value. This also reflects that traders' strategies in the gas market are spread-dependent. Meanwhile, our results indicate the threshold estimates also differ across the sub-periods considered in our analysis. This finding suggests that the transaction costs in the global gas market have been affected by the pandemic and geopolitical tensions, leading to changing threshold values. Furthermore, these threshold values vary for each price pair, reflecting the different underlying market forces affecting each pair. Finally, the results obtained from the time-varying Granger causality approach suggest that the leading role played by each benchmark may be dynamic and driven mainly by disruptive events or shocks that occur in the corresponding region. Such events include demand growth due to economic growth or policy changes, supply disruptions due to infrastructure outages, and geopolitical risks that may change the procurement structure and contractual agreements.

Our analysis provides some implications. First, the interdependence between the Asian and European gas markets, despite being influenced by external shocks, suggests that changes in one market's situation could affect the other. This highlights the importance of considering the broader market circumstances when assessing the supply security of each market. Therefore, bilateral policies between the two regions should be adopted to effectively manage demand and supply shocks. This may include sharing information on LNG trade flows, production levels, and demand forecasts. This would facilitate better coordination between the regions and enhance supply security amidst market fluctuations. Second, the decreased degree of integration between the US and the other two markets implies that the US market can promote the development of new liquefaction facilities to expand their export capacity further. This can increase the availability of LNG in global markets and help integrate the three regions. Third, high transaction costs and other arbitrage obstacles caused by external shocks should be taken into consideration to facilitate market integration. Therefore, market participants could incorporate more flexible pricing mechanisms and shorter-term delivery options in their traditional long-term LNG contracts to enhance market integration, reduce transaction costs, and increase liquidity. This is because spot and short-term trading in LNG are expected to increase, following its increasing pattern in the past decade. Finally, the time-varying Granger causal relationship implies that the predictive power of each regional gas benchmark should not be ignored because it might give useful and relevant pricing signals. Thus, it is necessary to fully understand the price discovery process and its dynamic behavior during periods of shocks in the respective region. Also, the time-varying Granger causality approach may provide a helpful tool for market participants in terms of price prediction and risk management.

Despite meeting the purpose of the analysis, it should also be noted that our study is not without limitations. The adopted non-linear co-integration approach assumes that the threshold value (the proxy for the transaction costs) is constant throughout the investigated period. However, if we expect the integration process in the gas market to change over time, the analysis should allow for time-varying thresholds. We try to avoid this limitation by running our analysis over the three sub-samples. Our suggestion about future research, which might be possible with more available data, could quantitatively investigate the different factors impacting the price differential between each price pair.

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Appendix

Appendix .1. Historical developments of natural gas supply and demand

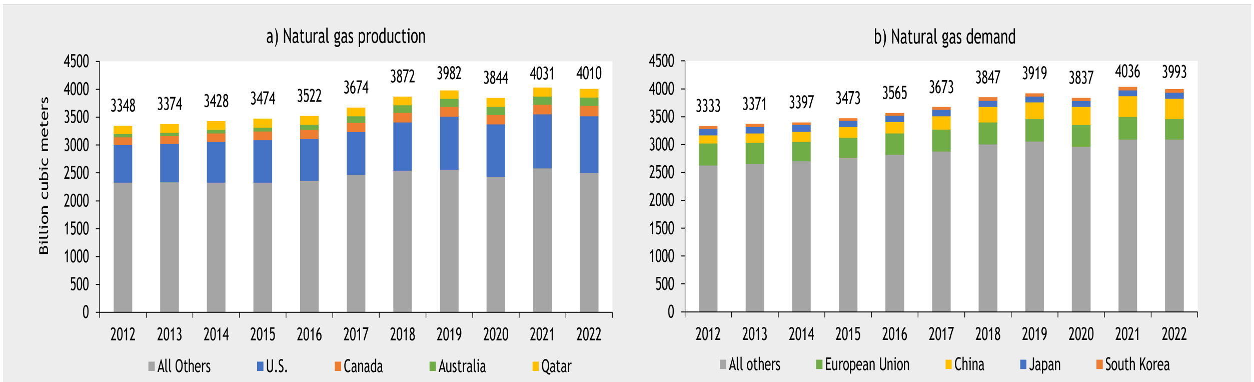

Figure (A.1) Worldwide and regional developments of natural gas a) production and b) demand from 2012 to 2022 (Billion cubic meters)

Appendix .2. Analysis of the entire time period 2016 - 2022

In this section, we provide further analysis of the entire sample from 2016 to 2022. The objective here is to gain some insights into the structural breaks that have affected the long-run relationship in the global gas market. To achieve this, we undertake two key steps: (1) testing the unit root properties of the three-time series; and (2) performing a co-integration test that considers multiple structural breaks.

We conduct three unit root tests, including the Augmented Dickey-Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The null hypothesis for ADF and PP tests is that the series has a unit root, while the null hypothesis for the KPSS test is that the time series is stationary. However, those conventional tests could result in incorrect conclusions in the presence of structural shifts, as they may falsely fail to reject the unit root hypothesis due to misspecification bias and size distortion, as highlighted by Perron (1989).To address this issue, we apply the Zivot and Andrews unit root test Zivot and Andrews (2002), which allows for the possible impact of structural breaks in the estimation period. This test is an adaptation of the Perron unit root test Perron (1989) and considers the endogenous presence of potential structural breaks in the series. In this analysis, both the structural break and the lag length are allowed to vary endogenously.

The results of the unit root tests are reported in Tables A.1 and A.2. The results of ADF, PP, and KPSS tests indicate that the time series are stationary in the first differences. This conclusion is further supported by the Zivot and Andrews unit root test, which considers the possibility of a structural break. This result suggests that even with the presence of a potential structural break, the series still exhibit an I(1) property.

Since the three price series are (1), we test the existence of co-integration between the pairs of natural gas price series. To accomplish this, we apply the Maki (2012) co-integration test, which is selected to handle

Table (A.1) Time series properties of natural gas prices

	ADF		PP		KPSS	
	Level	1st diff	Level	1st diff	Level	1st diff
EAX	-1.271	-14.645*	-1.554	-36.114*	2.794*	0.141
TTF	-1.378	-17.746*	-1.488	-39.983*	3.068*	0.231
HH	-1.872	-17.953*	-2.073	-44.219*	2.812*	0.142

Notes: The lag selection for ADF is based on Akaike Information Criteria (AIC). The test equations are estimated, including an intercept and trend for the variables in levels, whereas they include only an intercept for the first differences. * represents the 1% significance level. The three series are expressed in logarithms. The Critical values are obtained from MacKinnon (2010).

Table (A.2) Zivot–Andrews minimum t-statistics

	t-statistics	Break date
EAX	-2.907	26mar2020
TTF	-2.908	24mar2020
HH	-3.458	14may2020

Notes: Critical values are those reported in Zivot and Andrews (1992) as follows: CV(1%):-4.93 ;CV(5%): -4.42; CV(10%):-4.11

the potential presence of breaks in the long-term relationship. This test can identify up to five unknown breaks and is based on residuals, with the assumption that the number of breaks in the cointegrating vector is less than or equal to the maximum number of breaks.

According to the Monte Carlo simulations performed by Maki (2012), the proposed test outperforms previous methods (Gregory and Hansen, 1996a,b) when there are three or more breaks in the co-integration relationship. The test is also informed by the structural break tests of Bai and Perron (1998) and the unit root tests of Kapetanios (2005). Accordingly, each time period is considered as a potential structural break, t-statistics are calculated, and the dates with the lowest t-statistics are considered breakpoints.

Maki (2012) proposes four different models to test for cointegration with multiple breaks: model 1 considers multiple breaks in the intercept without a trend (level shift), model 2 considers multiple breaks in both the intercept and slope coefficients without a trend (level shift with trend), model 3 allows for multiple breaks in the intercept and slope coefficients with a time trend (regime shift), and model 4 accounts for multiple breaks in the intercept, slope coefficients, and trend (regime shift with trend). In this paper, we utilize models 3 and 4, which are specified as follows:

Model (3): regime shift

$$P_t^1 = \alpha + \sum_{i=1}^{k} \alpha_i D_{i,t} + \lambda t + \beta y_t + \sum_{i=1}^{k} \beta_i P_t^2 D_{i,t} + \alpha_{t,2} \quad (.1)$$

Model (4): regime shift with a trend

$$P_t^1 = \alpha + \sum_{i=1}^{k} \alpha_i D_{i,t} + \lambda t + \sum_{i=1}^{k} \lambda_i t D_{it} + \beta y_t + \sum_{i=1}^{k} \beta_i P_t^2 D_{i,t} + \alpha_{t,2} \tag{.2}$$

The results of Maki (2012) co-integration test with multiple structural breaks are estimated on the price pairs (EAX - TTF), (HH - EAX), and (HH-TTF). The results are shown in Table A.3, showing that the null hypothesis of no-co-integration is rejected. With regard to the structural breaks, we decided to concentrate on the dates that occur in the early months of 2020 and the latter months of 2021. These dates were selected due to the first break being associated with the demand shock caused by the pandemic, while the second break corresponds to the geopolitical tensions in the European market and restrictions on gas exports from Russia to the region.

Table (A.3) Results of Maki co-integration test with three breaks

Price pair		Test statistic	Break dates
TTF – EAX	Regime	-6.824***	2017-09-14; 2019-01-07;**2021-10-04**
	Regime with trend	-7.329***	**2020-04-23**; 2021-01-15; **2021-10-04**
HH – TTF	Regime	-5.416*	2019-12-20; 2020-12-25; **2021-09-17**
	Regime with trend	-6.511*	2018-07-17; **2020-03-27**; **2021-09-14**
HH – EAX	Regime	-5.969**	2019-03-05; 2020-12-25; **2021-09-29**
	Regime with trend	-5.277	**2020-03-24**; 2021-01-15; **2021-09-29**

Notes: Note: Critical values are obtained from Table 1 of Maki (2012). *, **, *** reveals the rejection of the null hypothesis of no cointegration.

Appendix .3. Description of the Shi et al. (2018, 2020) Time Varying Granger causality test

To examine the time-varying causal relationship among the three gas price series, we employ the recent causality procedure introduced by Shi et al. (2018, 2020). They develop three time-varying causality algorithms, namely forward recursive causality, rolling causality, and recursive evolving causality.

To estimate this procedure, suppose that Y_t is a vector, with the three gas price series, which can be estimated as follows:

$$y_t = \delta_0 + \delta_1 t + u_t \tag{.3}$$

With u_t follows this VAR(p) process:

$$u_t = \alpha_1 u_{t-1} + \alpha_2 u_{t-2} + ... + \alpha_p u_{t-p} + \epsilon_t \tag{.4}$$

Where ϵ_t is the error term. If we substitute $u_t = y_t - (\delta_0 + \delta_1 t)$ from Equ..4 into Equ..3, we get the following equation:

$$y_t = \rho_0 + \delta\rho_1 t + \alpha_1 y_{t-1} + ... + \alpha_p y_{t-p} + \epsilon_t \tag{.5}$$

Where ρ_i is a function of δ_i and α_j with i = 0,1 and j = 1,....,p.

To control for the integrated characteristics of our variables, the lag augmented VAR suggested by Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) is employed. It is a VAR model that is augmented with additional d lags to account for the possible maximum order of integration of the variables. This model is represented as follows:

$$Y = \lambda\Gamma' + X\Theta' + B\Phi' + \varepsilon \tag{.6}$$

Where Y $= (y_1, ..., y_T)_{T\times n'}$, $\lambda = (\lambda_1, ..., \lambda_T)_{T\times 2'}$, $_t = (x_1, ..., X_T)_{T\times np'}$, $x_t = (y_{t-}{}'_1, ..., y_{t-p'})$, $\Theta = (\beta_1, ..., \beta_p)_{n\times np}$, $B = (b_1, ..., b_T)_{T\times nd'}$, $b_t = (y_{t-p-1', ..., y_{t-p-d'})_{nd}}$, $\Phi = (\beta_{p+1}, ..., \beta_{p+d})_{n\times nd}$, and $\varepsilon = (\varepsilon_1, ..., \varepsilon_T)_{T\times n'}$, with d is the maximum oder of integration of y_t.

The heteroskedastic-consistent Wald statistic of the null hypothesis that variable 1 does not Granger cause variable 2 $H_0 : R_{1\Rightarrow 2}$ Π is given by

$$W_{1\Rightarrow 2} = [R_{1\Rightarrow 2}\hat{\theta}]'[R_{1\Rightarrow 2}(\hat{\Omega} \otimes (X'QX)^{-1})R'_{1\Rightarrow 2}]^{-1}[R_{1\Rightarrow 2}\hat{\theta}] \tag{.7}$$

Where $\hat{\theta}$ = vec($\hat{\Theta}$) represents the row factorization with $\hat{\Theta}$ is the OLS estimator $\hat{\Theta} = X'QX(X'QX)^{-1}$, $\hat{\Omega} = T^{-1}\hat{\varepsilon}'\hat{\varepsilon}$, and R is a m $\times$ n^2p matrix where m is the number of restrictions. The Wald statistic is asymptotically X^2_m under the null hypothesis.