Does oil price volatility delay natural gas infrastructure investment? Evidence from 1997-2025*

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Abstract

Price volatility delays irreversible investments like natural gas infrastructure. A possible contributor to such volatility is spillover from crude oil to natural gas markets. Previous studies have shown a declining trend in correlation of oil and natural gas volatilities. However, evidence is not yet available for how volatility spillovers have responded to recent market innovations. Therefore, the goal of this study was to analyze how volatility spillovers among US oil and gas spot prices change through 1997-2025. To this end, I use the Diebold-Yilmaz index on realized volatilities, DCC-GARCH for modeling correlation of returns, and the Bai-Perron structural break test on both return and volatility connectedness indices. Diebold-Yilmaz results show volatility spillovers are weak and have reduced from 1997-2025 with neither market being the dominant volatility transmitter. Likewise, DCC-GARCH shows small positive correlation among returns which further declines at the end of the sample. Together, these findings support independence of oil and gas market volatilities in a longer timeframe than formerly observed and suggest that oil market volatility is not a significant contributor to the natural gas infrastructure investment decision.

This Version: September 27, 2026

JEL Classification: [...]

Key words and phrases: [...]

*The authors are grateful... The usual caveat applies.

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1 Introduction

Compared to natural gas, petroleum transport and storage is relatively simple because oil is produced in liquid form. In contrast, natural gas depends on pipelines, specialized storage facilities and terminals for conversion to liquefied natural gas (LNG) for overseas trading (Liang et al., 2012) because it is a gas. Lack of such infrastructure has limited switching from crude oil to natural gas, leaving open an arbitrage where natural gas is much cheaper than oil in terms of underlying energy content (Liang et al., 2012; Brown and Yücel, 2008). At the same time, US citizens and policymakers are beginning to recognize that increasing energy supply is critical for supporting standards of living and to compete in the race for AI-driven industrial growth (Benich et al., 2026; Kay et al., 2026). To meet this energy need, it is important for the US to leverage its advantage as the highest producer of natural gas in the world (IEA, 2026), which involves construction of natural gas infrastructure in the near future. Despite the benefits to expanding the natural gas infrastructure network, volatile prices have quenched incentives for investment in transport networks because builders need to be certain the price will stay high enough to cover large upfront costs.

In particular, traditional firm investment theory suggests it is rational to invest if expected value is marginally higher than expected cost, but the real options literature shows this is not profitable in the case of sunk cost investments (Kellogg, 2014). Specifically, the real options literature shows the value of waiting to invest increases with expected price volatility holding expected return constant. Kellogg (2014) provides empirical evidence supporting this theory using firm-level data from the Texas oil drilling market. In this case, firms have reserved rights to a well but can wait to do expensive drilling and choose to wait longer when expected price volatility is high. Décaire et al. (2020) confirm Kellogg's findings within the natural gas drilling market. Likewise, natural gas infrastructure investments require large sunk costs (Von Hirschhausen and Neumann, 2008) and are therefore delayed by price volatility.

While applicable for all sunk cost investments, the price volatility disincentive is particularly important for the natural gas industry because gas is among the most volatile

commodities in the US economy. This volatility stems from multiple factors, including the seasonal, largely unpredictable, nature of demand and the difficulty to store natural gas (Liang et al., 2012). Natural gas in the US is mainly used for electricity and direct heating, whose consumption fluctuates wildly with season (Mu, 2007). Moreover, weather specifics are hard to forecast and regularly shock the market leading to price volatility (Mu, 2007). Regarding storage, gas is usually held underground with pipeline networks to add and withdraw gas (Rubaszek and Uddin, 2020), which contrasts with crude oil that is easily kept in barrels. Natural gas production is virtually constant across the year (Liang et al., 2012), so producers do a balancing act between how much they produce and how much they are able to store. If they produce beyond their existing storage capacity, they are forced to sell on the spot market and crash the price because short-run demand is inelastic (Nick and Thoenes, 2014; Gautam and Paudel, 2018). Instead of being dictated by global storage and demand as oil is, natural gas is mainly bounded local storage capacity and weather (Mu, 2007; Liang et al., 2012) which creates a very volatile market.

Beyond natural gas fundamentals, oil-to-gas volatility spillover may also be contributing to natural gas volatility (Ebrahim et al., 2014; Gong et al., 2021). Volatility spillovers occur when volatility in one asset creates volatility in another (Diebold and Yilmaz, 2012), which introduces uncertainty in the receiving market. Although oil is not as volatile as natural gas, it could have a significant effect on gas volatility if gas supply and demand depend on oil dynamics. For example, treasury rates are less volatile than stock prices, but significant volatility spillover is still found from treasuries to stocks (González-Urteaga et al., 2022). Interest rates are a primary determinant of corporate profitability and therefore uncertainty in the less volatile market influences uncertainty in the more volatile market. Similarly, a small amount of volatility in oil could create volatility in natural gas because of the coproduction and substitution relationships of the two products.

Regarding coproduction, oil and gas are often extracted together through traditional wells, or more recently, hydraulic fracturing (i.e., fracking). Fracking was developed in the

shale revolution where existing technologies were combined in new ways to recover oil and gas from previously unusable areas (Golden and Wiseman, 2014). The shale revolution began in the early 2000's and gained momentum around 2009 when US production began to show large increases (Sieminski, 2014). The first movers in the shale revolution were small firms (Golden and Wiseman, 2014), many of whom struggled during the Great Financial Crisis (GFC) and became consolidated at this time (Livingston, 2014). Coming out of the GFC, government stimulus led remaining businesses to flood the market with oil and gas (Al Suwailem and Selemankhel, 2021) which created a divergence between oil and gas spot prices because drillers treated natural gas as a byproduct of high-value oil production (Stern, 2020). The focus on oil over gas left producers willing to sell massive quantities of associated gas (i.e., gas which is extracted as a coproduct of oil) at any price, with total gas production doubling from 2005-2025 (EIA, 2026).

Beyond shared production, oil and gas markets may be tied because natural gas is often considered a substitute for refined petroleum products, with natural gas having advantages over petroleum through minimal refining, much cleaner burning, and relatively low prices (Liang et al., 2012). Historically, oil and gas have been imperfect substitutes with natural gas mainly used for direct heating through combustion and creating electricity (Liang et al., 2012) and petroleum typically refined into end products such as gasoline, diesel and heating oil (Jin and Xu, 2024; Kilian, 2016). While it is possible to use petroleum for electricity generation, burning gas is much more efficient (Oh et al., 2021), making natural gas dominant in this space (EIA, 2024) but with many plants carrying petroleum capacity to shield against gas price spikes (Gal et al., 2019). Moreover, natural gas competes with petroleum derivatives for residential and industrial heating and steam generation (Liang et al., 2012; Einstein et al., 2001). Both gas and petroleum are also inputs for plastics and petrochemicals, where the two energy sources are substitutable in the long run (Kapsalyamova and Paltsev, 2020). Similarly, in transportation, petroleum derivatives (e.g., diesel, gasoline, kerosene) have been dominant (EIA, 2019b), but technologies to switch from using oil to gas engines have existed

for a long time (Painuly and Parikh, 1993) indicating a potential for increased switching in the long run.

Given the economic connection of the two markets, studying oil-to-gas volatility spillover is useful to understand what factors firms are considering in the decision to invest in natural gas infrastructure. If oil-to-gas spillover is limited, then conflicts like the US-Iran war do not necessarily delay natural gas infrastructure development. Previous studies of volatility spillovers among oil and gas surrounding the shale revolution give mixed evidence regarding a disruption in market behavior. For the period covering the early 2000's, studies find bidirectional spillovers (Ewing et al., 2002; Lin and Li, 2015; Lovcha and Perez-Laborda, 2020), thereby indicating that the two markets were connected. After the shale revolution, studies generally find weaker spillovers (Lovcha and Perez-Laborda, 2020; Zhu et al., 2018; Gong et al., 2021) but differ on how much spillovers were reduced. For instance, Zhu et al. (2018) find near-zero spillovers with weak evidence of oil-to-gas spillover and no evidence of the reverse. In contrast, Gong et al. (2021) and Lovcha and Perez-Laborda (2020) study the periods of 2005-2019 and 1994-2018, respectively, and find evidence of some remaining spillover in periods following the shale revolution, but disagree on the dominance of oil versus gas, with Gong et al. (2021) finding oil as the dominant transmitter of volatility while Lovcha and Perez-Laborda (2020) find alternating dominance.

More recently, Kočenda and Moravcová (2024) finds low to moderate connectedness of volatility spillover across 1997-2023, with some elevation surrounding the Russia-Ukraine war. Regarding methods, early studies often adopted GARCH-BEKK (Ewing et al., 2002; Lin and Li, 2015) which has a clear interpretation of results for volatility spillover questions but is often computationally infeasible because of how many parameters are needed. For this reason, the GARCH literature has largely shifted towards DCC-GARCH (Efimova and Serletis, 2014) which reduces dimensionality and efficiently captures time-varying correlation of returns. However, in simplifying the model, the capacity to estimate volatility spillovers is lost. Therefore, the Diebold-Yilmaz connectedness index has emerged as a parsimonious

way to analyze volatility spillovers between oil and gas (Lovcha and Perez-Laborda, 2020; Gong et al., 2021; Kočenda and Moravcová, 2024) which is based on estimating a VAR with realized volatilities of both assets and conducting a Generalized Forecast Error Variance Decomposition (GFEVD) (Diebold and Yilmaz, 2012).

I contribute to the above literature by showing the time series of volatility spillover among oil and natural gas alone across an extended time span. Previous studies (Gong et al., 2021; Kočenda and Moravcová, 2024) which add more energy commodities to the Diebold-Yilmaz system have the benefit of showing connectedness within broad sectors (e.g., energy commodities), but have a tradeoff of blurring oil-gas dynamics. In contrast, Lovcha and Perez-Laborda (2020) applies Diebold-Yilmaz analysis to oil and gas futures alone, thereby giving a clear picture of spillover among these markets using daily total, directional and net spillover indices from 1994-2018. Most recently, Kočenda and Moravcová (2024) gives oil-to-gas and gas-to-oil spillover but does not show a time varying index, instead providing estimates in aggregated windows from 1997 to February 2023. Such aggregation often oversimplifies dynamics because volatility spillover tends to occur in clusters rather than in steady amounts across a window (Lovcha and Perez-Laborda, 2020; Diebold and Yilmaz, 2012). Therefore, I extend the time frame under consideration for weekly volatility spillovers among oil and natural gas spot prices for the US.

Finally, I estimate the DCC-GARCH model to consider the influence of oil price levels on natural gas price levels. Volatility spillover alone does not capture the influence that oil market shocks may have on natural gas infrastructure investment decisions because both expected volatility and expected return (which depends on the natural gas price level) form the decision to invest. Therefore, if the price levels among oil and gas are correlated, even lacking volatility spillover, then oil market shocks will influence the investment decision. To this end, I use the DCC-GARCH model to measure the correlation of oil and natural gas price changes, and choose this approach over alternatives (e.g., Diebold-Yilmaz index on returns) because both oil and gas returns exhibit conditional heteroskedasticity, which

is captured by DCC-GARCH. While other studies (e.g., Hasanli (2024) and Wang et al. (2025)) analyze correlation of returns over modern timespans, neither fully models effects of time-varying volatility on the dynamic correlation of returns.

Together, connectedness analyses over recent time spans for oil and gas markets are significant because of fundamental market changes which have been occurring in recent years, particularly a need for greater energy supplies. Specifically, the electricity reliability council of Texas (ERCOT) has reported they are expanding grid capacity at record speed to keep up with data center demand (EIA, 2025). Similar data center openings are happening all over the country, with estimates indicating 4% of US electricity consumption came from data centers in 2023 (Offutt and Zhu, 2025). To this end, data centers are connecting to local gas-powered grids at a breakneck pace, and some are even proposing to pipe in natural gas directly to generate power on-site (Bickel and Carr Smyth, 2026). Beyond domestic usage, more energy is needed outside the US due to geopolitical instability. For instance, LNG exports to Europe have increased following the Russia-Ukraine war and sabotage of the Nordstream natural gas pipeline running from Russia to Western Europe (EIA, 2025).

Therefore, the goal of this study was to analyze how volatility spillovers among WTI and Henry Hub spot prices change through 1997-2025. To this end, I estimate the Diebold-Yilmaz connectedness index (Diebold and Yilmaz, 2012) in one year rolling windows on realized volatilities of oil and gas prices to obtain total and directional spillover measures. Next, given the importance of time-varying volatility in crude oil and natural gas markets, I test previous findings of reduced correlation of returns among oil and gas (Dahl et al., 2012; Hasanli, 2024; Wang et al., 2025) using a DCC-GARCH model to control for effects of time-varying volatility. Finally, to determine if connectedness changes significantly across time, I use the Bai-Perron structural break test (Bai and Perron, 1998) on the indices for total volatility spillover and dynamic conditional correlation of returns. My results indicate that total volatility spillovers are low to moderate in strength across the sample period and have reduced since 1997. DCC-GARCH results also show weak time-varying positive correlation

of returns with near-zero correlation at the end of the sample. These findings are novel because they show independence of oil and gas market volatilities in a longer timeframe than previously observed, and add weight to reduced market connectedness along both price level and risk dimensions. This gives insight into the factors firms are considering in the expansion of gas infrastructure and suggest that effects of an increasingly uncertain crude oil market on the gas infrastructure space are limited.

2 Data

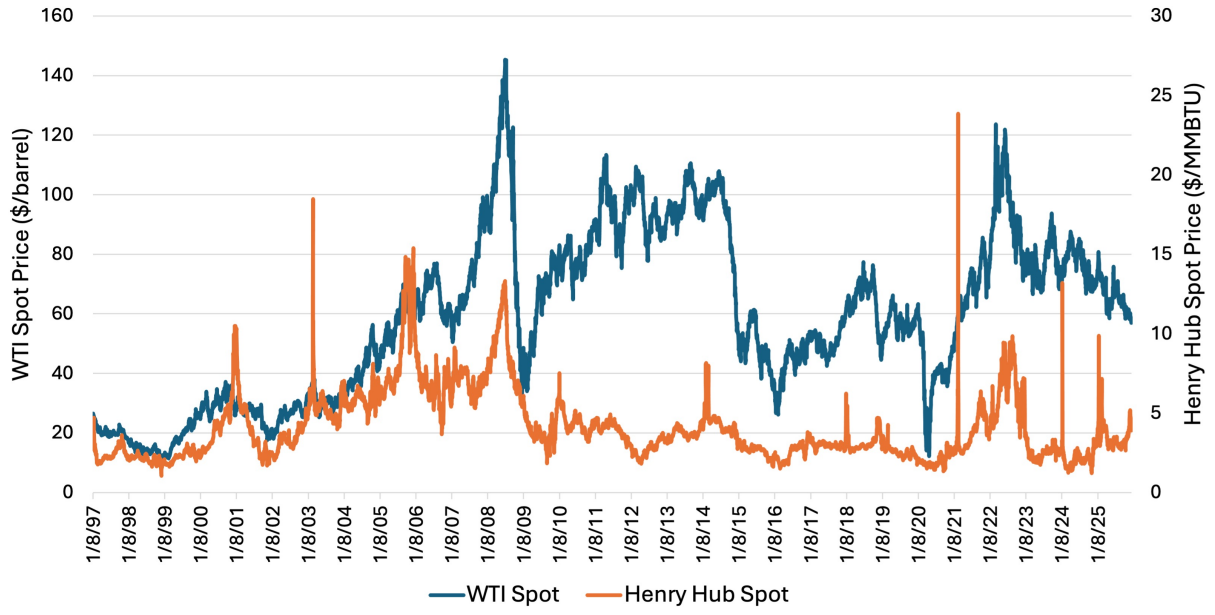


Figure 1: WTI Crude Oil and Natural Gas Spot Prices.

I use the West Texas Intermediate (WTI) crude oil spot[1] and Henry Hub natural gas spot prices,[2] both from the Energy Information Administration. The units of WTI spot are US dollars per barrel and Henry Hub spot are US dollars per million British thermal units (MMBTU). To clean these data, I keep dates where both price series are available, leaving a sample period of trading days from January 1997 – December 2025, shown in Figure 1 where

[1]Downloaded on 2025-12-28 from https://www.eia.gov/dnav/pet/hist/RWTCD.htm
[2]Downloaded on 2025-12-18 from https://www.eia.gov/dnav/ng/hist/rngwhhdD.htm

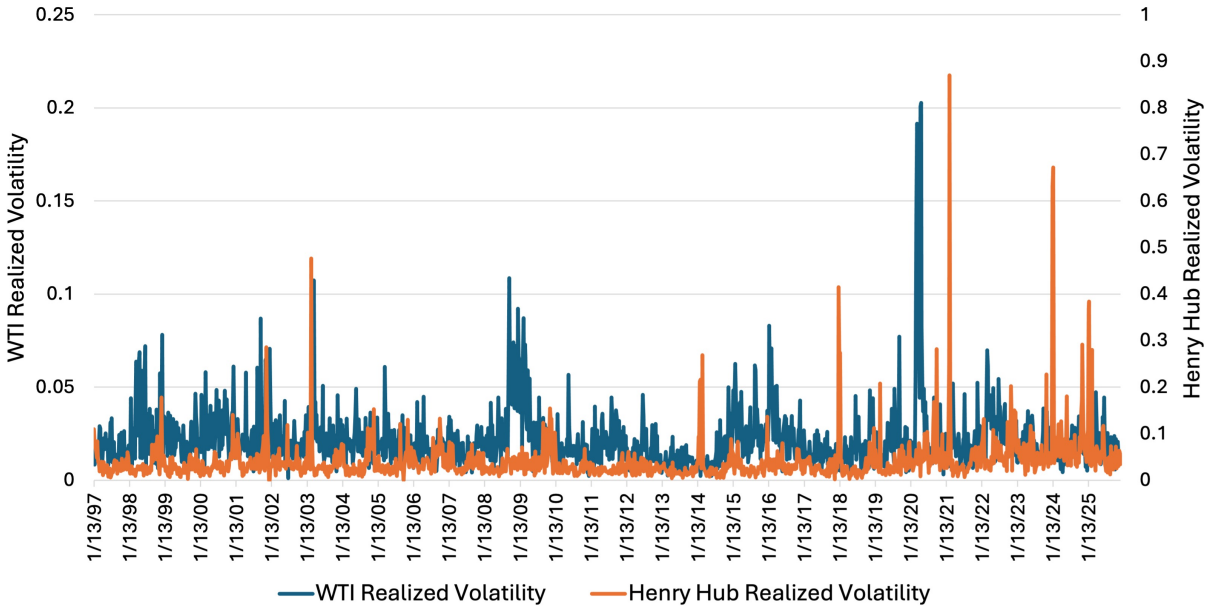


Figure 2: WTI Crude Oil and Natural Gas Realized Volatility.

before 2009 the two prices moved together but subsequently diverged, and towards the end of the sample, begin to converge.[3] Analyses use daily log returns and weekly realized volatilities which are calculated as the standard deviation of the log returns across every trading week (Monday-Friday) in the sample, resulting in 1507 weekly observations (Figure 2). I use weekly realized volatilities rather than calculating daily values with rolling windows (i.e., standard deviation across the previous observations for each day) as overlapping windows introduce serial correlation and thus a large lag length for the VAR in the subsequent analysis. To investigate the stationarity of the crude oil and natural gas returns and volatilities, I use the Phillips-Perron unit root test (Phillips and Perron, 1988), where the null hypothesis is that the time series has a unit root. I reject the null hypothesis of a unit root for both returns and volatilities.

[3]On April 20th, 2020, the WTI spot price went negative for the first time in history due to rapid demand decreases from the COVID pandemic and returned to positive values the following day (Bourghelle et al., 2021). The April 20th observation has been removed from Figure 1 and log returns from this observation were not calculated for April 20th and April 21st.

3 Methods

3.1. Diebold-Yilmaz Spillover Index

The Diebold-Yilmaz spillover index (Diebold and Yilmaz, 2012) is applied to volatility estimates to understand their overall connectedness and directionality of effects. To this end, I calculate the Diebold-Yilmaz spillover index in four directions:

1. Spillovers from natural gas to oil
2. Spillovers from oil to natural gas
3. Total spillover (1+2)
4. Net spillover (1-2)

In particular, consider a covariance stationary N-variable VAR(p)

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \tag{1}$$

where x_t is a vector of realized volatilities and ε_t is a vector of iid disturbances. The moving average representation is

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{2}$$

where the $N \times N$ coefficient matrices A_i obey the recursion

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + ... + \Phi_p A_{i-p} \tag{3}$$

with A_0 being an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$. The spillover indices are based on an H-step ahead GFEVD given by

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{4}$$

where a GFEVD is used instead of a traditional FEVD to make the results invariant to variable ordering in the VAR. Moreover, σ_{jj} is the standard deviation of the error term for the j-th equation, e_i is a selection vector with one as the i-th element and zero otherwise, Σ is the variance matrix for error vector ε and A_h is the $N \times N$ moving average coefficient matrix from the VAR of realized volatilities for the h-th lag. In a GFEVD, the row sum $\sum_{j=1}^{N} \theta_{ij}^{g}(H)$ does not equal one as it would in a traditional FEVD and therefore the decompositions are normalized as

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{5}$$

which makes $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. Equation (5) shows the percentage of forecast error variance (FEV) of variable i explained by shocks to variable j. This formula is rewritten as

$$S_{\cdot i}^{g} = \frac{100 \sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} = \frac{100 \sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \tag{6}$$

to show spillovers from market i to all other markets j as a fraction of total FEV (i.e., FEV of oil and gas markets combined which equals N from normalization above). Given the rescaling from equation (6), the directional spillover measures are bounded from zero to $100/N$ while total spillovers are bounded from zero to 100. Both directional and total spillovers show the magnitude of volatility connectedness relative to total FEV while net spillovers indicate differences in strengths of directional indices. Therefore, the units for net spillover change from percent of total FEV to percentage points (pp) which are bounded from -50 to 50. Both oil-to-gas and gas-to-oil spillovers are calculated across the entire sample in 52-week rolling windows (equivalent to one year) and are combined to produce total and net spillovers. A 52-week rolling window was chosen to control for seasonality within a year. Moreover, lag length $p = 3$ was selected by the BIC. Finally, given that H depends on what scale researchers want to analyze, there is no model selection used in the Diebold-Yilmaz literature for this parameter. Instead, it is common to choose a value based on economic reasoning (Diebold and Yılmaz, 2015) and to this end I use $H = 2$ weeks as a long enough

time frame for investors to shift among assets but short enough to clearly see directional effects.

3.2 DCC-GARCH

To test if expected returns to the natural gas infrastructure investment decision are influenced by oil price levels, I estimate a Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model (Engle, 2002). I choose a DCC-GARCH approach rather than alternative methods such as the Diebold-Yilmaz index on log returns to isolate the effect that directional price movements have on one another from effects of conditional heteroskedasticity (i.e., time varying volatility) which will appear in the univariate GARCH components but be omitted from the conditional correlation ρ_t through the standardization process of equation (15). Specifically, the conditional covariance matrix of returns is defined as

$$E_{t-1}(r_t r_t') \equiv W_t \tag{7}$$

and is decomposed into the product given by

$$W_t = D_t R_t D_t \tag{8}$$

$$D_t = diag\{\sqrt{w_{i,t}}\}, \tag{9}$$

$$w_{i,t} = E_{t-1}(r_{i,t}^2) \tag{10}$$

where D_t is a standard deviation matrix and R_t is the conditional correlation matrix. In particular, because the vector of oil and gas log returns r_t is 2×1 and the correlation of a variable with itself is always one, R_t can be rewritten as

$$R_t = \begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix} \tag{11}$$

where ρ_t is the dynamic conditional correlation of oil and gas standardized returns which I aim to estimate with DCC-GARCH. In addition to capturing a time-varying correlation of returns, each variable (oil log returns and natural gas log returns) individually follows a GARCH(1,1) specification which models current conditional variance as a function of last period's error and conditional variance. By fitting a GARCH(1,1) to both series, the DCC-GARCH is able to standardize the returns to control for time-varying volatility in both assets. In particular, the DCC-GARCH is formulated by

$$r_t|\mathcal{F}_{t-1} \sim N(0, D_t R_t D_t) \tag{12}$$

$$D_t^2 = diag\{\omega_i\} + diag\{\alpha_i\} \circ r_{t-1} r_{t-1}' + diag\{\beta_i\} \circ D_{t-1}^2 \tag{13}$$

$$\eta_t = D_t^{-1} r_t \tag{14}$$

$$Q_t = \Omega(1 - a - b) + a\eta_{t-1}\eta_{t-1}' + bQ_{t-1} \tag{15}$$

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1} \tag{16}$$

where $\circ$ denotes the Hadamard product of two identically sized matrices which is computed as element-by-element multiplication. The first equation assumes normality of returns conditional on past information to justify Maximum Likelihood Estimation (MLE) and the second equation shows each asset as following a univariate GARCH model. Moreover, ω_i is the unconditional variance for asset i, α_i is the ARCH coefficient for asset i, β_i is the GARCH coefficient for asset i, η_t is the vector of standardized returns which is mean zero and variance one for each series, Q_t is the conditional covariance of standardized returns, Ω is the unconditional covariance of standardized returns, a indicates how fast the correlation of returns responds to current shocks and b shows persistence of correlation. The DCC-GARCH model is estimated using two-stage Quasi-Maximum Likelihood Estimation (QMLE) where the GARCH(1,1) equations are estimated first, and the resulting coefficients are used to obtain the dynamic conditional correlation index.

3.3. Bai-Perron Structural Break Test

To test for changes in the connectedness of oil and natural gas volatilities I run the Bai-Perron structural break test (Bai and Perron, 1998) on a regression of the total spillover index from the Diebold-Yilmaz analysis on an intercept. Specifically, the purpose of this step is to determine whether there exist statistically significant differences in the level of volatility connectedness across the sample. In particular, I denote the total volatility spillover index calculated from the Diebold-Yilmaz analysis as y_t and consider a linear regression with m breaks ($m + 1$ regimes) given by

$$y_t = \delta_k + u_t \, (t = T_{k-1} + 1, ..., T_k) \tag{17}$$

where δ_k is a regime-dependent intercept with a separate value for each $k = 1, ..., m + 1$. Indices $(T_1, ..., T_m)$ are the unknown break points where I use the convention $T_0 = 0$ and $T_{m+1} = T$. To find the optimal breaks for a given m, all possible times of breaks $(T_1, ..., T_m)$ are run and selected by minimizing the sum of squared residuals. This is done for several break numbers m and the BIC is used to find the optimal number of breaks. Likewise, I check for structural breaks in the dynamic conditional correlation index ρ_t using a regression onto a regime-varying intercept.

I expect to see breaks in both return and volatility connectedness surrounding the shale revolution, consistent with past findings in the literature of a decoupling between crude oil and natural gas markets at this time (Dahl et al., 2012; Lovcha and Perez-Laborda, 2020). In particular, the shale revolution fundamentally changed the dynamics of oil and natural gas markets as large amounts of associated gas were produced beyond existing consumption capacity, leading to an adjustment period where natural gas was consumed in new ways (e.g., to increasingly power the growing US electrical grid – Appendix Figure A1). Moreover, previous studies have suggested a recoupling of markets at a new equilibrium leaving open the possibility of further breaks across the sample (Hasanli, 2024).

4 Results

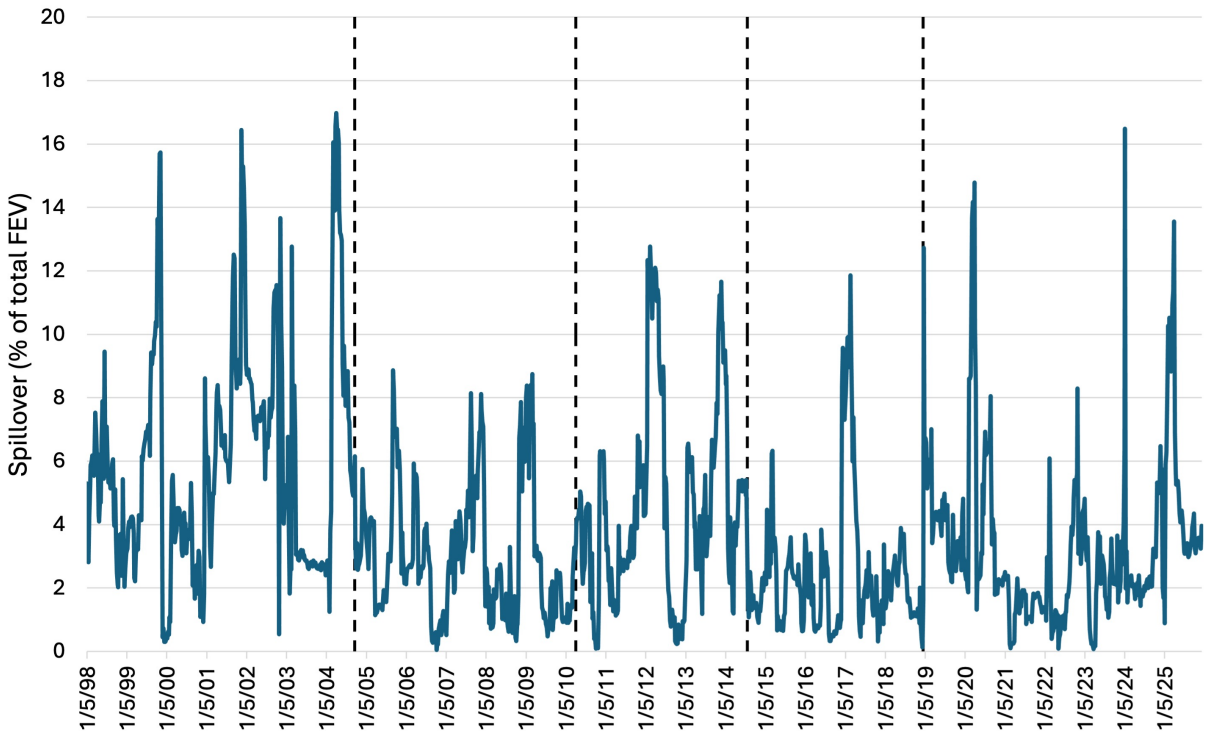


Figure 3: Diebold-Yilmaz total volatility spillover index. Vertical lines indicate structural breaks found by Bai-Perron test on weeks of 2004-09-20, 2010-04-05, 2014-07-21 and 2018-12-17.

Table 1: Summary of volatility spillover results within regimes identified by Bai-Perron test.

Regime	Start Date	End Date	Duration	Average Total Spillover (%)	Average Net Spillover (pp)
1	Jan 1998	Sep 2004	6.7 years	5.99	0.61
2	Sep 2004	Apr 2010	5.5 years	3.01	−0.21
3	Apr 2010	Jul 2014	4.3 years	4.55	0.31
4	Jul 2014	Dec 2018	4.4 years	2.42	0.25
5	Dec 2018	Dec 2025	7.0 years	3.34	−0.67

4.1. Diebold-Yilmaz Spillover Index

Figure 3 shows the total volatility spillover index where context for interpreting the units (percentage of total forecast error variance) comes from past applications of the Diebold-Yilmaz index in other markets. For instance, Diebold and Yilmaz (2012) study spillovers

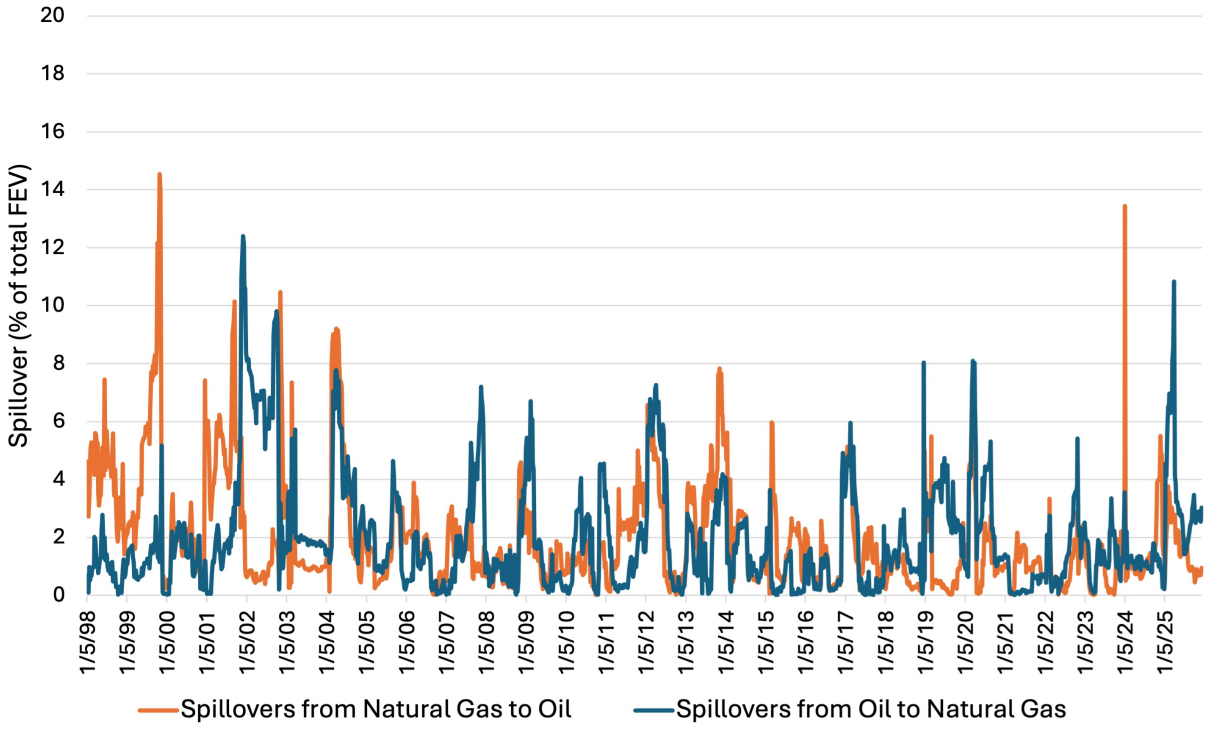


Figure 4: Diebold-Yilmaz directional volatility spillover indices.

between US stock, bond, currency and commodity prices and find that total spillovers range from 10-30%, on average being 12%, with highs of ∼30% reached during the GFC when there was significant transmission of risk information across markets. Additionally, Gong et al. (2021) use the Diebold-Yilmaz index to analyze oil and natural gas volatilities together with heating oil and gasoline, which brings the total spillover range to 35-60% indicating high connectedness. Given this scale, 5-10% total spillovers indicate mild connectedness between oil and gas volatilities, with above 10% total spillover being moderate.

Overall, Figure 3 shows that connectedness between oil and gas volatility is generally weak and declines over time, with total spillover typically ranging from 0% to 10%, occasionally exceeding 10%, and peaks of 17% occurred in March-April 2004 and January 2024 during times of geopolitical instability and a winter storm, respectively. However, even these sample highs are still within the moderate volatility spillover range given by past studies. Turning to the average total spillover within regimes identified by the Bai-Perron test in Table 1, the

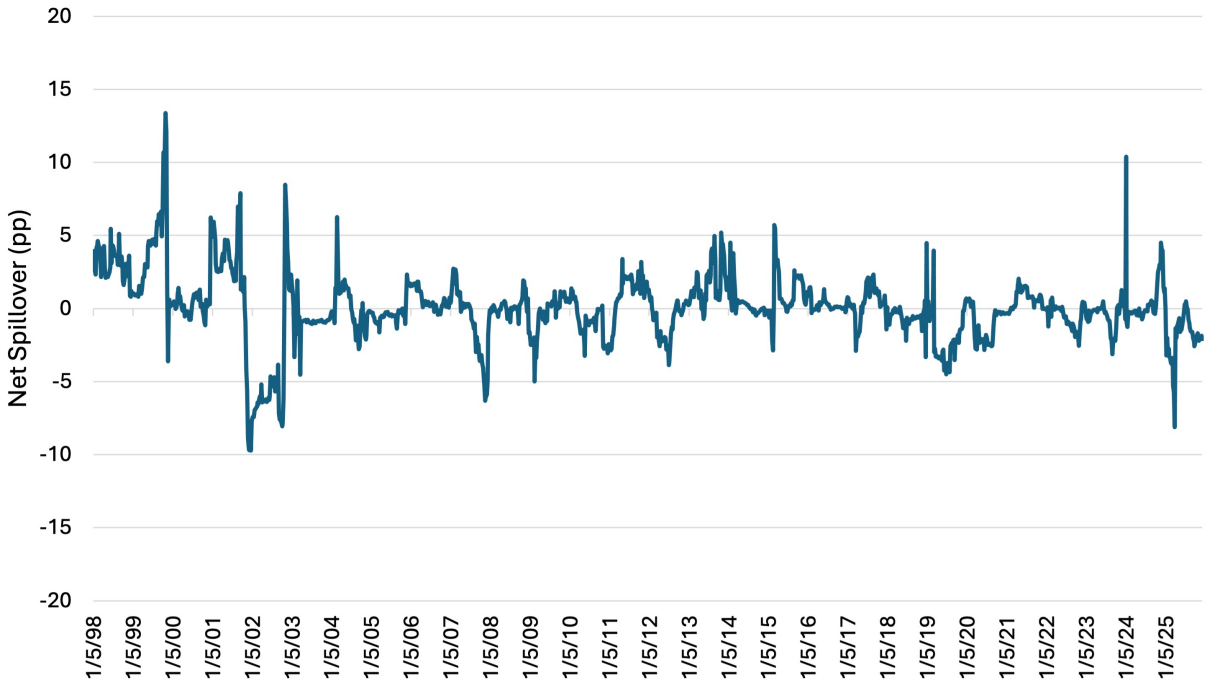


Figure 5: Diebold-Yilmaz net volatility spillover index. Positive values indicate gas-to-oil spillover is stronger than oil-to-gas spillover.

highest average total spillover of 6% in Regime 1 indicates mild connectedness and declines from there, going as low as 2% in the regime from 2014-2018, and ending on an average of 3% from 2018 to 2025.

The directional spillovers in Figure 4 show March-April 2004 was marked by relatively high gas-to-oil and oil-to-gas spillovers both, creating a compounding effect leading to total spillovers beyond 15% at various points across the period. At this time, the Afghanistan and Iraq wars were escalating (Sollinger et al., 2008), thereby increasing oil-to-gas spillovers from uncertainty in Middle Eastern oil supplies reaching the rest of the world, especially given that Iraq was an oil producer (Bamber et al., 2023). Moreover, the US was highly reliant on petroleum imports at this time, with imports peaking in 2005 (EIA, 2023), which plausibly increases the impact of oil volatility on other domestic markets (i.e., natural gas). In contrast, the later 17% total spillover value in 2024 was almost entirely a gas-to-oil spillover which is sensible as the major event in oil and gas markets at this time was a winter storm bidding up Henry Hub prices (Aniti, 2025). Regarding broader trends in the directional results,

equation (6) bounds the directional measures from zero to $100/N = 50$ while total spillover in Figure 3 is bounded from zero to 100, and given the rescaling, above 5% directional spillovers roughly indicate moderate connectedness. The oil-to-gas spillovers are generally low to moderate across the sample with the size of peaks decreasing over time. Likewise, the gas-to-oil spillovers tend to be weak with infrequent peaks across the early and late sample (e.g., January 2024 event).

Finally, net spillovers in Figure 5 show neither oil nor gas is the dominant transmitter of volatility, where positive values indicate that gas-to-oil spillovers are stronger than oil-to-gas spillovers (i.e., gas dominance). Net spillover stays approximately within a ± 10pp spillover range. Neither oil nor gas emerges as the dominant transmitter of volatility because periods of gas or oil dominance are limited to a handful of years. Moreover, while three of five regimes show positive average net spillover (Table 1), the magnitudes are not large enough to show dominance of either product. This is apparent from the range of net spillover in Figure 5. At its extremes, net spillover goes between ± 10pp, and in normal times, regularly goes between ± 3pp. Therefore, even the most extreme average net spillover is not large enough to indicate natural gas dominance.

Table 2: DCC-GARCH coefficients.

Parameter	Value	Std. Error
ω_n	0.29	0.056
α_n	0.14	0.011
β_n	0.86	0.011
$\alpha_n + \beta_n$	0.99	
ω_o	0.10	0.027
α_o	0.07	0.010
β_o	0.91	0.013
$\alpha_o + \beta_o$	0.98	
a	0.001	0.001
b	0.996	0.003
$a + b$	0.997	

4.2 DCC-GARCH

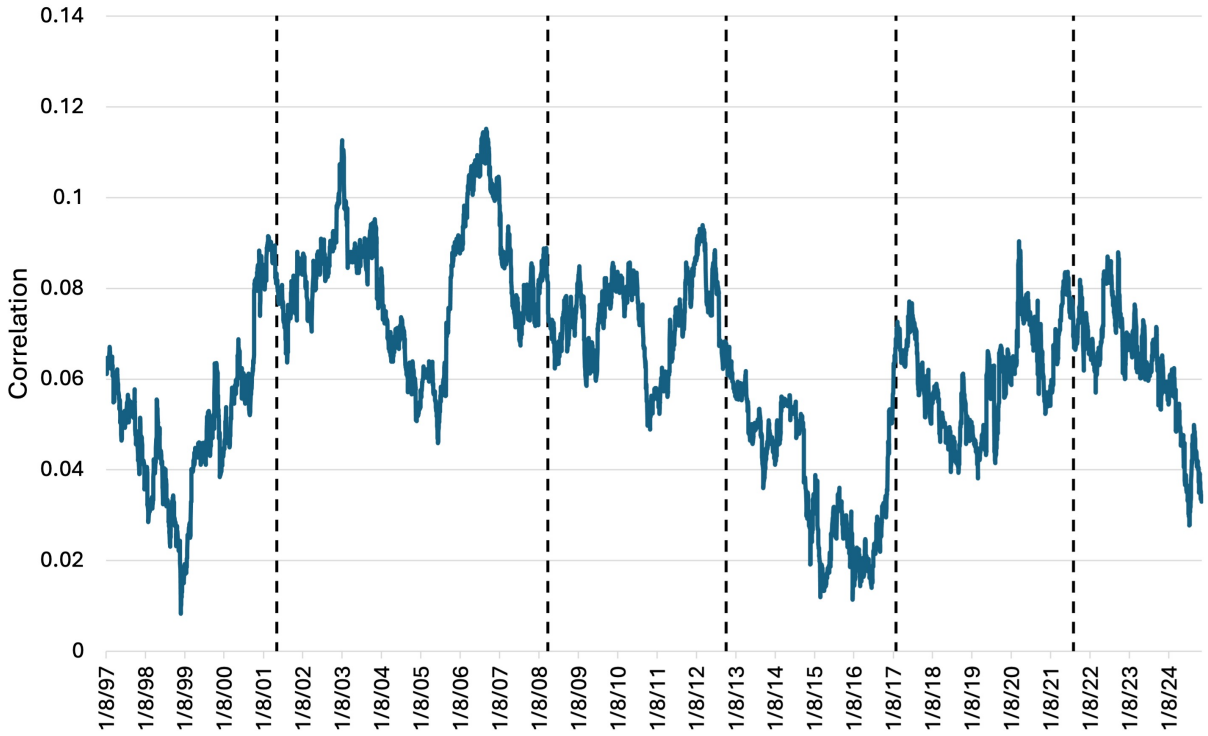


Figure 6: DCC-GARCH dynamic conditional correlation of returns index. Vertical lines indicate structural breaks found by Bai-Perron test on days of 2001-05-09, 2008-03-31, 2012-10-09, 2017-02-01 and 2021-08-05.

The DCC-GARCH model estimates correlation of returns controlling for time-varying volatility in oil and gas prices. The estimated volatility characteristics are summarized by the coefficients ω, α and β in Table 2 where subscript n indicates natural gas and subscript o indicates oil. Natural gas has a higher unconditional volatility $\omega_n = 0.29$ as opposed to $\omega_o = 0.10$ which is consistent with realized volatilities in Figure 2 where natural gas is more volatile than oil. Next, $\alpha_n = 0.14$ is larger than $\alpha_o = 0.07$ and $\beta_n = 0.86$ is smaller than $\beta_o = 0.90$, showing that natural gas volatility has greater response to initial price changes, but less persistence between periods compared to oil. Finally, $\alpha_n + \beta_n$ and $\alpha_o + \beta_o$ are both very close to one, indicating slow reversion to unconditional volatility. The properties of the conditional correlation of returns are summarized by parameters a and b in Table 2, where a is near zero and b is very close to one. This means that the correlation of returns is slow to respond to shocks but remains highly stable once shocked. Additionally, $a + b$ is very near

Table 3: Summary of dynamic conditional correlation results within regimes identified by Bai-Perron test.

Regime	Start Date	End Date	Duration	Mean DCC
1	Jan 1997	May 2001	4.3 years	0.0509
2	May 2001	Mar 2008	6.9 years	0.0816
3	Mar 2008	Oct 2012	4.5 years	0.0731
4	Oct 2012	Feb 2017	4.3 years	0.0386
5	Feb 2017	Aug 2021	4.5 years	0.0607
6	Aug 2021	Dec 2025	4.4 years	0.0556

one, indicating slow reversion to mean correlation.

Next, Figure 6 shows the estimated conditional correlation ρ_t of oil and gas standardized returns, where the average correlation is approximately 0.06. The conditional correlation shows some variation across time, with correlation dropping from the sample average to almost to zero in 1998, rising to sample highs of 0.11 in 2003-2006, declining to zero in 2015 and later rising to the range of 0.06 – 0.08 by 2020. The correlation once again begins to decline in 2023, going from 0.07 at the start of the year to zero by the end of the sample, suggesting an overall decoupling of the two markets.

Break tests show the highest average correlation (0.08) occurred between May 2001 and March 2008 during the onset of the shale revolution. The subsequent period (March 2008–October 2012) maintained a relatively high 0.07 correlation. Following this, the 2012–2017 period saw a low average of 0.04, followed by a rise to 0.06 (2017–2021) and a slight decline through 2025. Notably, ρ_t never reached strong correlation levels because from previous studies, even the sample high correlation value of 0.11 is still considered weak (Liao et al., 2018). While the 2001–2012 peaks suggest increased correlation of returns during the shale revolution where production changes affected producers involved in both industries, the magnitudes indicate that oil prices are not a primary driver of natural gas price expectations and thus infrastructure investment decisions. Recent declines in correlation further solidify this conclusion as indicated by the lower average and downward trend in Regime 6.

5 Discussion

I show daily volatility spillover among US oil and natural gas spot prices has reduced from 1997 – 2025, thereby extending the findings of previous studies which covered a shorter timespan (Lovcha and Perez-Laborda, 2020) or only gave oil-gas spillover results aggregated across time (Kočenda and Moravcová, 2024). Regarding magnitudes of previous studies, the 5 – 10% spillovers are consistent with the moderate time-varying connectedness between oil and gas futures found by Lovcha and Perez-Laborda (2020). Moreover, the total spillover index is lower than found by Gong et al. (2021), but the discrepancy can be explained by their inclusion of heating oil and gasoline, which plausibly increases connectedness given that the products are derivatives of crude oil. Finally, Kočenda and Moravcová (2024) show low average oil-to-gas and gas-to-oil spillovers from 1997 - February 2023, with the exception of moderate gas-to-oil spillover from February 2022 - February 2023 during the Russia-Ukraine war. I likewise find low average spillover across the aggregated windows in Table 1 but do observe periods of moderate spillover in disaggregated estimates (Figures 3-4).

The decrease in volatility spillovers across Figures 3-4 supports past findings of increased gas market independence (Gong et al., 2021; Lovcha and Perez-Laborda, 2020; Zhu et al., 2018). In particular, Lovcha and Perez-Laborda (2020) show that both oil-to-gas and gas-to-oil spillovers reduced after the Great Financial Crisis, which coincided with the shale revolution. Similarly, Gong et al. (2021) show that spillovers among petroleum products and natural gas futures prices reduced after the shale revolution, with the limitation that results are not shown for directional results (oil-to-gas and gas-to-oil spillover indices). Finally, Zhu et al. (2018) confirm these findings using Granger-causality models on implied volatility data from 2007 – 2015, showing little spillover overall, with no gas-to-oil spillover and limited oil-to-gas spillover. Together, these results suggest independence of oil and gas market volatilities, which I extend to cover more recent time periods.

The real options theory suggests investment in many natural gas infrastructure projects has been limited by price volatility. Infrastructure investment may be increasing despite

the price volatility in recent years because the natural gas price has been rising from improvements in the efficiency of natural gas generators (Hasanli, 2024), external demand from Europe through LNG exports (Di Bella et al., 2024) and increased power needs from data centers (EIA, 2025). However, transmission of volatility from oil to natural gas could be a serious threatening factor to producers given that any source of volatility brings into question whether their investment will remain profitable. My finding of low volatility spillovers indicates that the firm decision to delay natural gas infrastructure investments is not influenced by oil price volatility. Therefore, models of infrastructure investment decisions can be simplified to a function of natural gas fundamentals rather than oil market volatility. This study extends the finding of volatility independence to a longer time period, which is important because recent changes in oil and gas markets could have shifted the spillover relationship.

Next, I show that neither oil nor natural gas is the dominant transmitter of volatility. The oil-to-gas and gas-to-oil spillover indices tend to be of similar magnitude with periods of positive or negative net spillover limited to a handful of years. The finding that neither oil nor gas is the dominant transmitter shows that risk transmission depends on the specific type of shock rather than always coming from the same market. This contrasts with past findings of oil-to-gas volatility spillovers being stronger than gas-to-oil spillovers (Gong et al., 2021). Oil dominance is sensible because oil has historically been the more valuable commodity in the coproduction relationship, and due to this, coproducers made production decisions using oil prices, which led to changes in natural gas supply (Stern, 2020). Moreover, oil price volatility has previously signaled economic instability (Ebrahim et al., 2014) which affects natural gas demand through reduced industrial production. Although having been a useful signal in the past, oil volatility as a macroeconomic driver may be an outdated concept given that use of other energy inputs has increased as a share of overall energy consumption since the 1950's-70's, for instance, when oil price increases signaled future recessions (Hamilton, 1983). Therefore, a possible explanation of reduced oil-to-gas volatility spillover is that energy

use has become more dispersed among different products. My results are consistent with Lovcha and Perez-Laborda (2020) who find alternating spillover dominance and attribute the presence of gas-to-oil spillovers to increased financialization and capacity to profit from existing arbitrages. It is possible that volatility in the US gas market both leads consumers to switch among oil and gas for short-term gains and creates general economic uncertainty.

Finally, DCC-GARCH results show that correlation among returns is weakly positive with a decline at the end of the sample consistent with previous findings that oil and gas price levels are increasingly independent of one another (Dahl et al., 2012; Hasanli, 2024; Wang et al., 2025). Early evidence from the oil-gas ratio indicated that if oil rises then natural gas will eventually increase (i.e., natural gas will have a price floor if oil is high – Brown and Yucel 2008), but that appears outdated because oil prices were high after the shale revolution and natural gas prices were very low (Hasanli, 2024). A lack of price coupling is useful information for producers because it signals that diversification among these energy sources is valuable, specifically through shared wells compared to pure natural gas or oil plays because when one price goes down the other does not necessarily drop. Moreover, my findings suggest that natural gas price levels, and thus expected returns to infrastructure investments, are not strongly influenced by oil prices. While previous studies such as Hasanli (2024) and Wang et al. (2025), covering 1997 – 2022 and 2016 – 2023, respectively, extend to a similar timespan as my study, the DCC-GARCH results show that their findings of weakened correlation of price levels are robust to controlling for time-varying volatility across the two markets.

The results from the Diebold-Yilmaz index could be described as lack of risk coupling while the DCC-GARCH output could be interpreted as lack of price coupling. A finding of low market connectedness across both models indicates that the assets neither move together nor destabilize one another. In contrast, it appears most natural gas volatility comes from natural gas fundamentals (e.g., weather, storage). In the real options framework, oil market shocks influence neither the expected price volatility of natural gas nor the expected

returns to the infrastructure investment, which suggests that oil market shocks are not a significant contributor to the natural gas infrastructure investment decision. Moreover, the oil market is becoming increasingly uncertain now given widespread geopolitical instability from the Russia-Ukraine and US-Iran wars. Since the US natural gas market is broadly local with most gas consumed in the US being produced domestically (EIA, 2019a), natural gas producers may be willing to invest in domestic natural gas infrastructure despite global conflicts because the natural gas space is not heavily influenced by oil.

A limitation of the current study is that the data is restricted to US oil and gas markets, which was chosen because the US is currently among the largest producers and consumers of energy in the world, recently becoming an oil exporter due to the shale revolution (EIA, 2023). Because natural gas is primarily a regional commodity, it is sensible that the relationship between oil and gas will be different by country, so future studies are needed to examine this. Moreover, future studies could track oil volatility spillovers into more local natural gas spot markets within the US. Furthermore, I limit my analysis to spot instead of futures markets as a gauge on fundamental factors related to these commodities as opposed to more complex dynamics affecting futures related to interest rates and trading of paper contracts whose intent is never to be called for delivery (Cheng and Xiong, 2014; Pindyck, 2001). Therefore, future studies should compare volatility spillover results using spot and futures contracts.

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A ADDITIONAL DATA

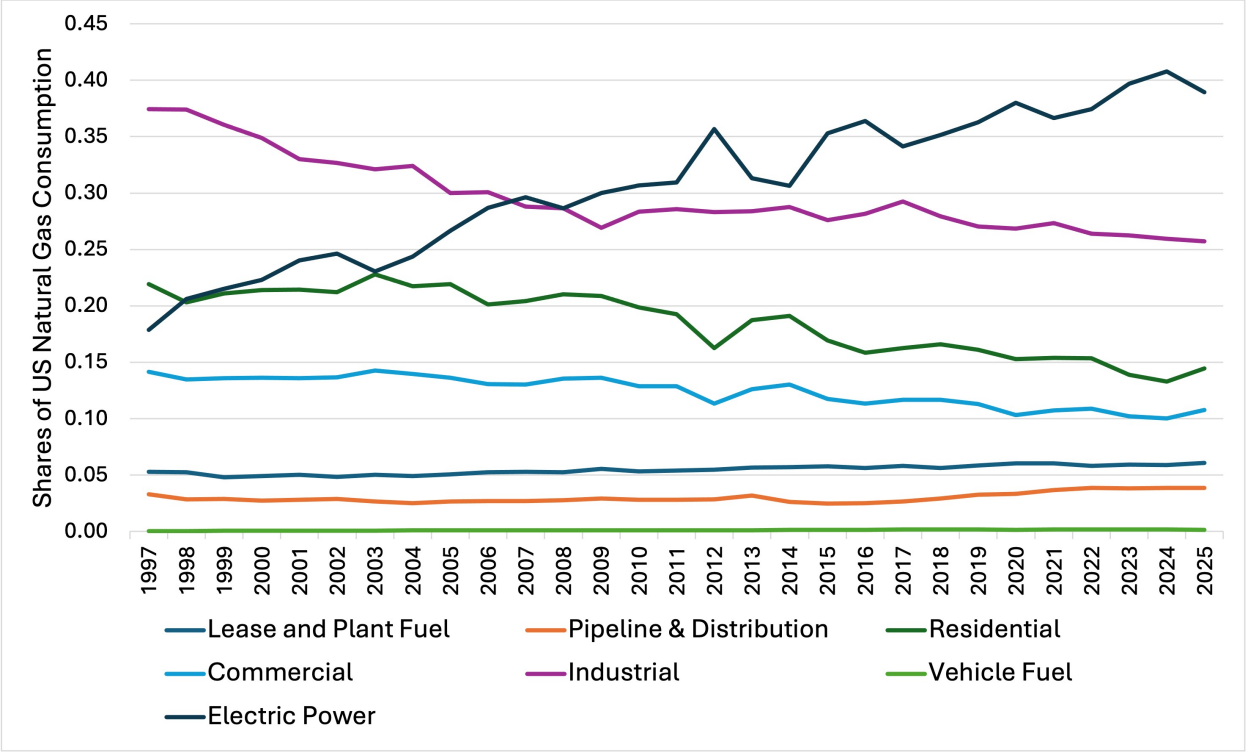


Figure A.1: US natural gas consumption shares from EIA data at this link