Price Connectedness in U.S. Biodiesel and Petroleum Diesel Markets

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Abstract: This study quantifies market integration across U.S. biodiesel plant-level and wholesale markets, as well as between biodiesel and petroleum diesel wholesale markets. Using Diebold-Yilmaz (2012, 2014) connectedness measures and a rolling window approach, we examine how price connectedness evolves across regions and supply chain levels. We find strong intra-supply chain integration within biodiesel markets and substantial cross-market integration between biodiesel and petroleum diesel wholesale markets. Connectedness declines sharply post-2022, coinciding with the renewable diesel boom as established supply chain interactions and regional price dynamics shift to reflect new market conditions.

Keywords: Market integration; Forecast error variance decomposition; Supply chain; Market fundamentals; Renewable diesel boom

1. Introduction

The biodiesel boom has transformed renewable fuel markets over the past two decades, with biodiesel production expanding significantly (e.g., Irwin and Good, 2013). This period of rapid growth was primarily driven by policy incentives and environmental concerns as the United States sought to decarbonize its transportation sector (McCormick and Moriart, 2023). The Renewable Fuel Standard (RFS), introduced in 2005 and expanded in 2007, played a central role in this transformation by mandating minimum renewable fuel volumes in the nation's fuel supply (EPA, 2017). Biodiesel production was modest prior to the RFS, amounting to just 112 million gallons in 2005, but grew to over 1.8 billion gallons by 2020, a 16-fold increase (EIA, 2024). This expansion firmly positioned the U.S. as one of the world's largest producers and consumers of biodiesel.

Blending mandates promoted the development of a supply chain, from biodiesel production to biodiesel blending with the ultra-low sulfur diesel (ULSD) and the distribution of the final product. Biodiesel and ULSD markets became strongly connected through shared infrastructure and overlapping demand. When the biodiesel boom began to wane around 2020, another boom emerged in renewable diesel. Renewable diesel is a "drop-in" replacement for petroleum diesel derived from the same renewable feedstocks as biodiesel, with production and consumption growing rapidly since 2021. Renewable diesel can directly substitute for ULSD without blending and is likely to alter well-established supply chain interactions and regional price dynamics.

This article investigates market integration in the biodiesel supply chain and how it has changed over time. In a first stage, we measure integration using the price connectedness framework proposed by Diebold and Yilmaz (2014). In a second stage, we identify the dynamics of connectedness and its drivers, with special attention to the renewable diesel boom. We complement the connectedness analysis with Johansen cointegration tests to confirm that the markets maintain long-run equilibrium relationships, establishing that the short-run connectedness patterns captured by the Diebold-Yilmaz (DY) framework operate within a cointegrated system. Price connectedness quantifies how price volatility shocks propagate across different markets, with higher connectedness suggesting more integrated markets. Highly integrated markets transmit price signals and enable optimal resource allocation, while segmented markets hinder price discovery and increase costs. We examine both regional integration (across different geographic markets) and vertical integration (between plant-level production and wholesale distribution) to provide a comprehensive view of the biodiesel supply chain.

The Diebold and Yilmaz (2012, 2014) connectedness framework relies on forecast error variance decompositions (FEVD) from a Vector Autoregression (VAR) model that captures price relationships. We assess both static and dynamic connectedness, with the latter relying on a rolling window approach. This methodology reveals the strength and evolution of price interdependencies in the biofuel supply chain, showing how price volatility shocks propagate across the system. Our data consist of weekly plant level biodiesel prices and daily wholesale biodiesel and petroleum diesel prices from January 4, 2013, to May 10, 2024.

Our analysis incorporates regional integration by examining key U.S. markets: i) Upper and Lower Midwest, West and East Coast, and South Central regions for plant-level biodiesel; ii) Chicago, New York, and the Gulf Coast for wholesale biodiesel; and iii) Chicago, New York, Gulf Coast, and Los Angeles for wholesale petroleum diesel. These markets form critical nodes in the biodiesel supply chain, encompassing production, blending, and distribution networks that shape national fuel prices.

Examining price connectedness across the entire supply chain reveals how shocks originating at any market and stage propagate through other markets. By analyzing interactions between biodiesel and petroleum diesel wholesale markets, we highlight the broader economic and policy implications of their interdependence, particularly as renewable fuels increasingly compete with and complement traditional petroleum products. We then investigate the underlying drivers of price connectedness, by focusing on market fundamentals — production, imports, exports, feedstock costs, and policy instruments like the D4 Renewable Identification Number (RIN) prices. We further consider the renewable diesel production data to investigate how the renewable diesel boom is impacting this connectedness.

The existing literature on price connectedness in energy markets has largely focused on crude oil, natural gas, and electricity. A common finding is the critical role of supply-side factors, policy interventions, and global trade in shaping price links (e.g. Liu and Gong, 2020; Broadstock et al., 2020; Ji et al., 2018; Ma et al., 2022). In the biofuels literature, research has primarily focused on ethanol and its price relationships with agricultural feedstocks such as corn. Findings emphasize the importance of feedstock prices in driving price dynamics (Trujillo-Barrera et al., 2012; Gardebroek and Hernandez, 2013; Kristoufek et al., 2016; Gerveni et al., 2023b). Some studies highlight the strong long-term relationships between biodiesel and feedstock prices such as soybean oil and rapeseed oil, though they often focus on European markets, leaving U.S. biodiesel markets less explored (Hassouneh et al., 2012; Abdelradi and Serra 2015).

Research on biodiesel and its interaction with petroleum diesel remains relatively sparse. Tanaka et al. (2023) find long-term linkages between biodiesel, petroleum diesel, soybean oil, and crude oil in the U.S. Their study relies on a single price series for each market, limiting insights into regional differences and supply chain dynamics. Our work extends this literature by incorporating multiple regional markets and supply chain levels, providing the first comprehensive analysis of price connectedness across the U.S. biodiesel supply chain and its relationship with petroleum diesel markets.

Beyond the research gap in U.S. biodiesel markets, the existing literature also employs methodological approaches that differ from ours. Hassouneh et al. (2012) employ multivariate local linear regression alongside parametric vector error correction models to capture asymmetric price transmission among biodiesel, sunflower oil, and crude oil prices in Spain, while Cárdenas, Gutiérrez, and Otero (2017) use Pesaran's (2007) pairwise convergence tests to examine whether diesel prices across French petrol stations maintain stable long-run relationships. Our research questions how price connectedness within and across the biodiesel supply chain has evolved over time, and what market fundamentals and policy instruments drive it. Answering these questions requires a framework that can simultaneously quantify directional spillovers across multiple regional markets and supply chain levels, identify net transmitters and receivers of shocks, and track how these transmission patterns change over time. Unlike approaches designed for small systems of two or three prices or pairwise tests that establish whether prices converge but not how shocks propagate, the DY connectedness framework scales naturally to our multivariate setting and provides the directional, time-varying spillover measures needed to characterize the network structure of price transmission within and across biodiesel and ULSD markets. We further supplement the DY analysis with Johansen cointegration tests to confirm that the markets maintain long-run equilibrium relationships, bridging the short-run connectedness evidence with the spatial market integration literature.

Our results reveal significant integration between biodiesel production plants and wholesale hubs. Wholesale biodiesel markets emerge as dominant transmitters of price shocks underscoring their critical role as national distribution hubs. Regional dominance is similarly distributed across Chicago, Gulf Coast and New York wholesale markets, consistent with their roles as centers of production, blending and consumption centers, respectively. The Upper Midwest leads among plant-level markets due to its status as the largest biodiesel production hub. The West Coast functions as a net receiver of price connectedness, reflecting its reliance on external supply chains and the impact of localized regulatory frameworks, such as California's Low Carbon Fuel Standard (LCFS) and Oregon and Washington’s Clean Fuels Programs.

Our findings also uncover significant integration between biodiesel and USLD wholesale markets. Gulf Coast and New York ULSD markets emerge as the largest net transmitters of price connectedness across both biodiesel and ULSD wholesale hubs. The Gulf Coast USLD market is not only the largest blending and distribution center, but is also a key ULSD consumption hub, enhancing its national influence. The New York USLD market influence derives from its location in a major consumption and distribution region.

Our regression analysis identifies that market fundamentals and policy instruments strongly correlate with biodiesel market integration. While policy support and increased production increase price connectedness, renewable diesel production reduces it by functioning as a direct substitute for both biodiesel and petroleum diesel. In particular, the renewable diesel boom weakens market integration in biodiesel and ULSD wholesale markets, reducing information flows across traditional biodiesel markets.

Our research is novel in quantifying market integration in the biodiesel supply chain and its drivers. We provide valuable insights into this critical energy market. Our findings illuminate how market fundamentals and policy interventions shape price transmission across the fuel supply chain. Our analysis is particularly timely with the ongoing renewable diesel boom and allows us to anticipate a progressive shift of price discovery centers away from current biodiesel and ULSD markets as renewable diesel markets grow.

2. Market Background and Data

Our analysis examines both plant-level and wholesale markets to understand price connectedness throughout the biodiesel supply chain, as well as the relationship between biodiesel and petroleum diesel markets. Plant-level production involves the conversion of feedstocks into biodiesel through a transesterification process (Mumtaz et al., 2017). After production, biodiesel is stored in on-site tanks or regional storage facilities before being transported to wholesale terminals using railcars, trucks, or barges. At the wholesale level, biodiesel is blended with petroleum diesel to produce biodiesel blends, typically between 5 and 20 percent. Wholesale terminals also serve as key hubs for distributing both pure biodiesel (B100) and blended biodiesel to retailers and end-users.

Data availability primarily determines our collection frequencies. We collect weekly plant-level prices to capture regional production dynamics and daily wholesale prices to reflect the more liquid trading environment at wholesale distribution hubs. Weekly spot B100 plant-level prices for seven U.S. regions—West Coast, South Central, Upper Midwest, Lower Midwest, Northeast, Southeast, and Rocky Mountain—are from ts. Regional boundaries are shown in Figure 1. Fastmarkets reports Friday high and low prices based on completed transactions, and the midpoint for each region. We use the midpoint of high-low ranges for our analysis.

According to the U.S. Energy Information Administration (EIA), the U.S. had 55 biodiesel plants in 2023. Figure 1 shows the location of each plant, with dots scaled in size according to production capacity. Table 1 provides additional detail by region, highlighting the Upper Midwest dominance with 23 plants, 42% of the national total. Other regions contain between 6 and 7 plants, except the Rocky Mountain region, which, according to the EIA, has no biodiesel plants.[1] We thus exclude the Rocky Mountain region from our empirical analysis. Geographical concentration in the Upper Midwest reflects proximity to feedstock sources, particularly soybean oil, which accounts for approximately 55% of biodiesel feedstock usage (Gerveni et al., 2024). The Upper Midwest produces over 80% of total U.S. soybeans output (USDA, 2025) and attracts biodiesel plant investment because feedstock costs constitute the largest share of biodiesel production costs

[1] The Fastmarkets price for the Rocky Mountain region is presumably computed based on prices for adjacent regions.

(Carriquiry et al., 2014). Plants locate strategically near major soybean-processing facilities to minimize transportation expenses and ensure a stable feedstock supply.

In 2023, the U.S. biodiesel industry had a total nameplate capacity of 2.1 billion gallons, with the Upper Midwest accounting for 54% (1.12 billion gallons), mirroring plant distribution. Total U.S. biodiesel production in 2022 of 1.6 billion gallons utilized approximately 78% of capacity.[2] The Upper Midwest emerges as the largest producing region with 55% of the national total. The South Central region follows with 297 million gallons (18%). Smaller contributions come from the Lower Midwest and West Coast, each producing approximately 150 million gallons (9%), and the South East and Northeast each accounting for 4% of total US production.

Biodiesel consumption follows a different regional pattern than production (Table 1). The Upper Midwest leads in both metrics, accounting for 28% (456 million gallons) of total U.S. consumption. The West Coast emerges as the second largest consumer (26% at 425 million gallons) despite its limited production. The significant consumption levels in the West Coast stem from high population density and stringent environmental policies, including LCFS and similar policies in Oregon and Washington, which create relatively strong demand for biodiesel. Meanwhile, the South Central region, home to many refineries and blending terminals, ranks third at 18% of U.S. biodiesel consumption. This distribution suggests that while production is concentrated near feedstock sources, consumption is driven by population density, transportation sector demand, and state policy frameworks.

Turning to the wholesale level of the biodiesel supply chain, we analyze daily spot B100 wholesale prices from the Oil Price Information Service (OPIS) for three major terminals: Chicago, New York, and Gulf Coast. These terminals are strategically positioned to connect production centers to major consumption markets. Chicago, located in the Upper Midwest, connects the largest biodiesel production hub to the rest of the country. The Gulf Coast, in the South Central region, is a major hub for both biodiesel and petroleum diesel markets, enabling blending operations and exports. New York, in the Northeast, is a major distribution center and a key hub for imports. OPIS

[2] The latest year for which state-level biodiesel production is available from the EIA is 2022. The state-level estimates are used to construct the regional-level production estimates.

reports daily high and low prices for each market based on completed transactions. When no trades occur on a given day, OPIS applies a "highest bid/lowest offer" methodology. This method uses the open deals posted but not traded by the end of the day to assess daily prices. Consistent with plant-level biodiesel price data, we use the midpoint of the high and low prices reported by OPIS daily.

Because biodiesel is frequently blended with petroleum diesel, these markets influence each other through substitution effects and shared infrastructure. Understanding petroleum diesel markets is thus essential to our analysis of price connectedness. Figure 2 shows that in 2022 the U.S. had 127 petroleum refining complexes. The data in Table 2 indicates that the South Central region dominates with 43% of all refineries, largely due to the Gulf Coast's refining infrastructure. Since diesel is refined from crude oil, its production is naturally concentrated in regions with significant crude oil refining capacity, ensuring an efficient supply chain from crude extraction to final fuel distribution. The West Coast is the second largest, accounting for 20% of petroleum refineries, with remaining regions hosting between 6% and 12% each.

Petroleum refinery operating capacity closely mirrors the regional distribution of refineries, totaling 271 billion gallons. The South Central region accounts for 57% of total operating capacity, reflecting its role as the largest refining hub in the country, serving both domestic and international markets. The West Coast follows with 15% of national operating refining capacity, with other regions ranging from 3% to 9%.

Unlike the concentrated production patterns, Table 2 shows that petroleum diesel consumption is more evenly distributed across regions, reflecting variations in transportation demand. Of the 61 billion gallons consumed nationally in 2022, the South Central region leads at 21.4%, supported by its role as a major refining and distribution hub. The Northeast ranks second (17%) due to high population density and large transportation demand. The remaining regions contribute between 5% and 16% each.

For petroleum diesel, we analyze daily spot wholesale prices from OPIS for four major ULSD terminals: Chicago, New York, Gulf Coast, and Los Angeles. These coincide with the terminals for biodiesel, except Los Angeles, which lacks sufficient B100 wholesale price data for our analysis. These terminals represent critical distribution points for both petroleum diesel and biodiesel blending operations, linking production and refining centers to consumption areas. Among them, Los Angeles operates as a distinct market as the LCFS influences ULSD pricing and its distribution.

Overall, both biodiesel and petroleum diesel markets concentrate production near their primary feedstocks—biodiesel in the Upper Midwest due to soybean oil availability and petroleum diesel in the South Central region near crude oil refining hubs. However, consumption is more evenly distributed according to transportation needs. Wholesale terminals bridge these geographical gaps by linking production centers to demand regions, facilitating price information flows throughout the supply chain. Our connectedness analysis quantifies these price relationships and reveals how shocks propagate through these markets.

3. Methodology

Here we provide a description of the Diebold and Yilmaz (2012, 2014) connectedness framework. Consider a covariance stationary *N*-variable Vector Autoregression of order *L* VAR(L), expressed as:

$$x_t = \sum_{l=1}^{L} \Phi_l x_{t-l} + \varepsilon_t \tag{1}$$

where *L* is the order of the VAR model, x_t is the *N* x 1 vector of endogenous prices, Φ_l is an *N* x *N* coefficient matrix, and $\varepsilon_t \sim (0, \Sigma)$ is an i.i.d. error term with covariance matrix Σ. The Moving Average (MA) representation of the VAR(L) is:

$$x_t = \sum_{l=0}^{\infty} \psi_l \varepsilon_{t-l} \tag{2}$$

with ψ_0 being an *N* x *N* identity matrix and $\psi_l = \Phi_1 \psi_{l-1} + \Phi_2 \psi_{l-2} + \cdots + \Phi_L \psi_{l-L}$. The transformation of the VAR(L) into its MA representation, re-expresses the N-variable system from a function of lagged prices (eq. 1) to a function of past shocks (eq. 2). The moving average coefficients (ψ_l) of those shocks capture how innovations propagate through the system over time, and are key to understanding the dynamics of the system.

Connectedness measures are approximated through *H*-step-ahead FEVD. The forecast horizon *H* determines how far ahead we look when measuring how shocks influence the future price variance. The FEVD parses each variable's forecast error variance into portions attributable to its own shocks and to shocks originating from other variables in the system. This decomposition is important, as it quantifies how relevant particular price shocks are in explaining the variance of others. Diebold and Yilmaz (2012, 2014) use the generalized FEVD framework of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998). This framework produces variance decompositions invariant to ordering. It does not require orthogonalized shocks; rather, it allows and accounts for correlated shocks using the historically-observed error distribution, under a normality assumption.

We denote by $\theta_{ij}(H), i, j = 1, \dots, N$, the ij^{th} H-step FEVD component, which measures the fraction of variable $i's$ H-step FEVD due to shocks in variable j. So, i is the receiving variable and j the transmitting variable. In our context, this measures how price shocks in one biodiesel or petroleum diesel market affect price forecast error variance in another market. $\theta_{ij}(H)$ can be expressed as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \psi_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \psi_h \Sigma \psi_h' e_i\right)} \tag{3}$$

where σ_{jj} is the standard deviation of the error term ε_j, e_j is a selection vector whose j^{th} element equals 1 and the rest equal zero.

Because shocks are not orthogonalized in the Generalized FEVD framework, the sum of the contributions to variable i's forecast error variance derived from shocks to each variable in the system does not necessarily equal one, i.e., $\sum_{j=1}^{N} \theta_{ij}(H) \neq 1$. Diebold and Yilmaz (2012, 2014) normalize each $\theta_{ij}(H)$ by the sum $\sum_{j=1}^{N} \theta_{ij}(H)$, i.e.,

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \tag{4}$$

which results in $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and by construction, $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$.

The full set of H-step-ahead generalized FEVD, denoted as $\tilde{\theta}_{ij}(H)$, produces what we call the connectedness table (see Table 3). The upper-left $N \, x \, N$ block comprises the full matrix of *pairwise directional connectedness measures*, $D = [\tilde{\theta}_{ij}(H)]$, and each element is interpreted as a percentage. Rows (i) measure the connectedness received by each market and columns (j) the connectedness transmitted by each market. The pairwise directional connectedness from j to i is denoted $S_{i \leftarrow j} = \tilde{\theta}_{ij}$, while from i to j is $S_{j \leftarrow i} = \tilde{\theta}_{ji}$. In general, $S_{i \leftarrow j} \neq S_{j \leftarrow i}$, hence there are N^2 −N separate pairwise directional connectedness measures. They are analogous to bilateral price information flows between each pair of markets.

We can also quantify the *net pairwise directional connectedness*, which represents the balance of price influence between two specific markets. It is the difference between connectedness transmitted by market *j* to each other market *i* minus connectedness received by market *j* from each other market *i*, $S_{ij} = S_{i \leftarrow j} - S_{j \leftarrow i}$.

The off-diagonal row sums in Table 3, labeled "*From others*", capture *total directional connectedness received by market* i *from all other markets* j*,* $i \neq j$*,* quantifying a market's overall price sensitivity to external influences. :

$$S_{i \leftarrow \blacksquare}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 \tag{5}$$

Row sums including diagonal values, labeled "*From others including own*," capture total directional connectedness received by market i from all other markets and from itself. Because the generalized FEVD are row-normalized, each row of the connectedness table sums to 100%, meaning the forecast error variance of each variable is fully attributed across its own and others' shocks.

The off-diagonal column sums, labeled "*To others*", capture total directional connectedness transmitted by market j to all other markets i*,* $i \neq j$*,* measuring a market's overall price influence on external markets:

$$S_{\blacksquare \leftarrow j}(H) = \frac{\sum_{\substack{i=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{\substack{i=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 \tag{6}$$

Column sums including diagonal values, labeled "*To others including own*," measure total directional connectedness transmitted by market j both to the rest and to itself. However, each column sum, including own contributions, is not constrained to equal 100. So, entries in the "*To others including own*" row can exceed 100%.

We can also quantify the *net total directional connectedness* as the difference between the total connectedness transmitted by market j to others minus the total connectedness received by market j from others, which identifies whether a market is predominantly a transmitter or receiver of price shocks: $S_j = S_{\blacksquare \leftarrow j} - S_{j \leftarrow \blacksquare}$.

Finally, the value in the lower right corner of the table presents the total connectedness index, which is the ratio between the grand off-diagonal column (or row) sum and the grand row (or column) sum including diagonal values, expressed as a percentage of total variation:

$$S(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} = \frac{\sum_{\substack{i,j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100 \tag{7}$$

This total connectedness index quantifies the overall degree of market integration. For example, if the total connectedness index, $S(H)$, for the full sample period is 60%, this indicates that 60% of the total variance of the forecast errors for all variables in a system is explained by the connectedness of shocks across variables, whereas the remaining 40% is explained by idiosyncratic shocks.

The DY connectedness framework described above captures short-run price spillover dynamics but, does not directly test long-run price convergence. To complement the connectedness analysis, we conduct Johansen cointegration tests (Johansen, 1988; Johansen and Juselius, 1990) on the log-transformed price series at both the wholesale and plant levels. The Johansen procedure tests for the number of cointegrating relationships (r) among multiple price series by examining the rank of the long-run impact matrix through two likelihood ratio tests — the trace statistic and the maximum eigenvalue statistic. Finding cointegration among regional prices would confirm that these markets share common stochastic trends and maintain long-run equilibrium relationships, providing the structural foundation for interpreting the short-run connectedness patterns captured by the DY framework as evidence of market integration.

4. Results

This section presents the research results in four subsections, the first (subsection 4.1) being devoted to summary statistics, subsections 4.2. and 4.3 to connectedness measures and 4.4 to the drivers of connectedness.

4.1 Summary Statistics

Table 4 provides summary statistics of the weekly B100 plant level prices and daily B100 and ULSD wholesale prices across different U.S. markets and terminals, during the period from January 4, 2013 to May 10, 2024. While in the empirical analysis we use the first difference of log prices to ensure stationarity, induce normality, and reduce heteroskedasticity (Bierlen et al.,1998), prices in Table 4 are in $/gallon to facilitate interpretation.

B100 wholesale and plant level prices in every terminal and market are nearly twice as expensive as ULSD prices due to the higher production costs of biodiesel. On average, B100 prices are $4.05 per gallon, compared to $2.20 per gallon for ULSD (Table 4). Approximately 80% of biodiesel production costs are driven by the high prices of feedstocks such as vegetable oil, animal fats, and used cooking oil that are essential for biodiesel production. Cost differentials explain the consistent price premium of biodiesel over ULSD.

Plant-level B100 prices exhibit regional variation, with the West Coast reporting the highest average ($4.47) compared to production-intensive regions like South Central ($3.86) and Upper Midwest ($3.96). Price differences are likely to be caused by transportation costs from major production centers to main consumption hubs. Wholesale B100 prices show a narrower range ($4.02-$4.10) across terminals, with relatively small differences between Chicago, New York, and Gulf Coast markets. ULSD wholesale prices range from $2.15 to $2.24 across terminals. Figure 3 reveals strong co-movement among all price series throughout the study period, with biodiesel consistently maintaining its premium over ULSD, while wholesale prices typically exceed plant-level prices due to additional distribution costs.

4.2 Cointegration Tests

Before measuring and analyzing short-run B100 and ULSD price connectedness patterns, we examine the long-run integration properties of the price series, to establish whether the DY connectedness measures can be interpreted as evidence of market integration. Table 5 reports the Augmented Dickey-Fuller (ADF) unit root test results for all B100 plant-level, B100 wholesale, and ULSD wholesale log price series for January 4, 2013 to May 10, 2024. All thirteen series fail to reject the null hypothesis of a unit root in levels but reject it in first differences at the 1% significance level, confirming that each series is integrated of order one, I(1). This satisfies the prerequisite for meaningful cointegration testing and justifies the use of first-differenced log prices in the subsequent DY connectedness analysis.

Table 6 presents the Johansen cointegration test results for five market systems, organized from individual systems (Panels A–C) to cross-system tests (Panels D–E), over the period January 4, 2013 to May 10, 2024. Panel A indicates four cointegrating vectors among the six B100 plant-level regional markets, implying two common stochastic trends and strong spatial integration, with the two independent pricing forces likely reflecting geographic and feedstock cost differentials. Panels B and C each indicate a single common stochastic trend within the B100 and ULSD wholesale markets, respectively, consistent with spatially integrated markets where regional price differentials are stationary in the long run. Panel D indicates at least four cointegrating relationships across the biodiesel plant and wholesale system, confirming that price signals transmit effectively between production and distribution in the long run. Panel E indicates at least three cointegrating relationships across all seven B100 and ULSD wholesale markets, confirming significant cross-fuel long-run price linkages consistent with the shared distribution infrastructure that connects biodiesel and petroleum diesel markets.

These cointegration findings provide the structural foundation for interpreting the short-run connectedness patterns analyzed in the following subsections. Because the markets are cointegrated—within fuel types, across supply chain levels, and across fuel types—the price spillovers captured by the DY framework reflect transmission dynamics within genuinely integrated markets.

4.3 Static Price Connectedness Results

We apply Diebold and Yilmaz (2012, 2014) connectedness framework using *H*-step ahead generalized FEVD to measure price relationships within biodiesel markets and between biodiesel and petroleum diesel markets. In this subsection we present the results from using the whole sample, from January 4, 2013 to May 10, 2024, and denote them as static results. In subsection 4.4, we use a rolling window approach that allows to observe the dynamics of connectedness over time.

We study connectedness by analyzing two distinct market systems. The first system includes the six biodiesel plant-level markets (Lower and Upper Midwest, Northeast, Southeast, South Central and West Coast) and the three biodiesel wholesale markets (Chicago, New York and Gulf Coast). This analysis reveals how shocks propagate spatially and through different supply chain levels. To align weekly plant-level with daily wholesale prices, we aggregate wholesale prices to weekly frequency by sampling wholesale prices each Friday. The second system focuses on the three B100 wholesale markets and the four ULSD wholesale markets (Chicago, New York, Gulf Coast and Los Angeles). This analysis assesses cross-region and cross-fuel interdependencies. This connectedness analysis uses daily price data.

Connectedness measures are based on VAR models. We work with the first difference of log prices to ensure stationarity, consistent with the results in the previous section. We use the Schwarz Bayesian Criterion (SBC) and Bayesian Information Criterion (BIC) to determine the VAR order, resulting in orders ranging from 1 to 2, depending on the specific model. Tables 7 to 10 present key connectedness measures for each price system: connectedness transmitted by market j to each other market i, $S_{i\leftarrow j}(H)$; connectedness received by market i from each other market j, $S_{j\leftarrow i}(H)$; net connectedness from market j to i, $S_{ij}(H) = S_{i\leftarrow j}(H) - S_{j\leftarrow i}(H)$, and the grand total connectedness $S(H)$ reflecting overall market integration. Connectedness measures are derived for a forecast horizon of H = 10 weeks (plant-level) and H = 50 days (wholesale-level) based on two criteria. First, both horizons are long enough to ensure that the price system fully absorbs informational shocks. Impulse-response analysis of the underlying VAR models shows that price responses dissipate within 4 weeks (plant-level) and within 5 days (wholesale-level). Second, H = 10 weeks corresponds exactly to 50 weekdays, maintaining a consistent real-time comparison across data frequencies. Sensitivity analysis presented in the Online Appendix confirms that the total connectedness measures are robust to the choice of forecast horizon across all three systems.

Each of the tables is divided into four quadrants: diagonal quadrants show the within-group connectedness (e.g. plant-to-plant or wholesale-to-wholesale), while off-diagonal quadrants show between-group-connectedness (e.g., plant-to-wholesale or B100-to-USLD). Subsections 4.3.1 and 4.3.2 present the results for the first and second price systems.

4.3.1 B100 at the Plant and Wholesale Market Level

The total connectedness index for the combined B100 plant-level and wholesale markets is 78.5%, indicating that over three-quarters of forecast error variance stems from price interconnections between these markets (Table 7). This high level of connectedness demonstrates that price shocks propagate throughout the biodiesel supply chain rather than remaining isolated in specific markets.

The three wholesale markets are the most influential with gross transmission rates between 91.2% and 92.7%. These markets are also the largest net transmitters, with total net connectedness values ranging between 17.49% and 19.95% (Table 8). These results highlight wholesale markets' pivotal role in incorporating and distributing price information to both plant-level and wholesale markets nationwide. Results align with Ferrer et al. (2018), who demonstrated that centralized hubs dominate short-term connectedness transmission in energy markets, reflecting their importance in blending operations and central location.

Among the plant-level markets, the Upper Midwest is the most influential in propagating price shocks (85.1%, Table 7), which is consistent with its substantial share of biodiesel nameplate capacity (54%). The Upper Midwest is also the only net transmitter among the plant-level markets, with a total net connectedness of 3.97% (Table 8). However, the Upper Midwest remains a net receiver from wholesale markets with pairwise net connectedness fluctuating between -2.62 to -1.91%. This dynamic illustrates the Upper Midwest comparative advantage as a production hub due to its proximity to soybean oil supplies, which minimizes costs and establishes its significance in regional price-setting (Haas et al., 2006). Its dependence on wholesale hubs for national price dissemination is consistent with Busse et al. (2012) who observed similar hierarchical dynamics in biodiesel supply chains, where production hubs influenced upstream pricing but relied on downstream nodes for broader price transmission.

All the other plant-level markets are net receivers with net values ranging from -25.04 to -2.92 (Table 8). The West Coast exhibits distinctive behavior as the largest net receiver of price connectedness. The West Coast has also the highest level of self-generated connectedness among all regions, with 24.11% (this value is generated from the difference between 74.97% and 50.86%

in Table 7) of its price movements driven by internal factors. This reflects its geographical isolation from major production centers. Local factors, such as transportation costs and regulatory differences, seem to play a significant role in shaping West Coast price dynamics. Particularly, the LCFS sets a carbon intensity reduction target for transportation fuels, incentivizing the use of biodiesel and renewable diesel. Oregon and Washington have also adopted Clean Fuels Programs with comparable carbon intensity reduction goals. Our results are consistent with Romano and Scandurra (2012) who observed that more isolated markets like the West Coast exhibit slower price pass-through.

Finaly, the Diebold-Yilmaz framework does not weight prices by regional production volume or capacity prior to estimation, so it captures each market's price influence endogenously through the estimated VAR dynamics and forecast error variance decompositions. The resulting connectedness measures confirm that the Upper Midwest — which accounts for 55% of national biodiesel production and 54% of nameplate capacity (Table 1) — is the only net transmitter among all plant-level markets. This alignment between the framework's endogenously determined connectedness rankings and the independently observed regional market characteristics suggests that the unweighted price series effectively reflect underlying differences in market size and influence.

In sum, wholesale markets transmit and receive more connectedness among themselves than from plant-level markets, highlighting their cohesive national distribution network. Plant-level markets also interact more strongly within their own group, reflecting more localized price dynamics driven by regional production factors. This segmentation emphasizes the distinct economic roles of production hubs versus wholesale markets in the biodiesel supply chain.

4.3.2 B100 and ULSD at the Wholesale Market Level

The total connectedness index for the combined B100 and ULSD wholesale markets is 72.3%, highlighting significant integration between these markets. Tanaka et al. (2023) found similar interactions between crude oil, soybean oil, and biodiesel markets, reflecting how price dynamics in renewable fuels are influenced by blending and substitution relationships with conventional petroleum products.

ULSD Gulf Coast and New York dominate the system, with 88.6% and 87.8% of their FEVD being transmitted to other markets (Table 9). The Gulf Coast's prominence reflects its position as a central hub for refining and exporting petroleum diesel, accounting for 57% of total US crude oil refinery capacity (Table 2). New York's significance stems from its location in the Northeast, the second largest ULSD consuming market with 17% of total US consumption. These results align with findings by Ferrer et al. (2018) and with Bhanja et al. (2021), with the latter highlighting that dominant energy hubs like the Gulf Coast amplify market volatility and redistribute price signals, acting as benchmark-setting nodes in fuel markets. While the ULSD Gulf and New York markets are the primary transmitters of price connectedness in the system, the B100 Gulf and Chicago markets also play notable roles, transmitting 79.5% and 71.1% of their FEVD. The B100 Gulf Coast benefits from both biodiesel and ULSD infrastructure, including blending and export operations, while Chicago connects Upper Midwest biodiesel production with national B100 and ULSD wholesale markets.

In terms of net connectedness (Table 10), the ULSD Gulf Coast (+13.7) and New York (+13.0) are the only two net transmitters among the ULSD markets, reinforcing their pivotal role in redistributing price shocks. Among the B100 wholesale markets, the Gulf Coast (+6.9) and Chicago (+1.0) are also net transmitters, although to a lesser extent.

Despite this strong interaction, the ULSD and B100 wholesale markets exhibit notable segmentation. Both market types transmit and receive more connectedness within their own groups than across fuel types. Cross-market connectedness flows primarily from ULSD to B100 markets rather than vice versa, reflecting the relative size and dominance of the petroleum diesel market. This segmentation may arise from differences in supply chain structures, market participants, or regulations.

4.4 Dynamic Price Connectedness Results

While Section 4.3 analyzed static price connectedness, this section shifts focus to a time-varying perspective to assess how market integration has evolved over time and identify market-specific responses to external shocks, particularly the emergence of renewable diesel as a competing fuel.

For clean interpretation of results, we examine dynamic price connectedness separately within each market segment (B100 plant-level prices, B100 wholesale prices, and ULSD wholesale prices). We re-estimate the VAR model and connectedness measures using prices within each group exclusively and derive the grand total, measuring overall market integration in each stage.[3]

A rolling window approach is implemented that allows dynamic adjustment to structural breaks and evolving market conditions. We use a fixed window of 52 weeks for plant-level and 260 days for wholesale-level data, advancing one day/week at a time. This generates 2,439 subsamples from the total number of observations (2,699). We follow Diebold and Yilmaz (2012) and test VAR stability within each window based on eigen values and find that all but two of the models for plant-level windows and all of the models for the wholesale level are stable. We delete the two non-stable windows for the plant level from the dynamic analysis. As before, we derive the connectedness measures for each rolling windows based on the assumption of an N-dimensional covariance stationary data generating process.

Figure 4 presents the time-varying total price connectedness indices for the three groups: B100 plant-level markets (Panel 4a), B100 wholesale markets (Panel 4b), and ULSD wholesale markets (Panel 4c). The vertical axis measures the magnitude of connectedness and the horizontal axis measures time, with each point on the horizontal axis representing connectedness based on 52 weeks of plant-level and 260 days of wholesale-level data. Each observation thus contains approximately one year of data.

The figure suggests substantial fluctuations in connectedness over time, with notably different patterns across market segments. Biodiesel markets at both plant and wholesale levels show high connectedness during the COVID-19 period, followed by a moderate decline in 2022-2023. This decline coincides with the rapid growth of renewable diesel production beginning in 2021. ULSD wholesale markets display a similar patterns, with connectedness dropping from 73% to below 68% by late 2022.

The decline in connectedness after 2022 for biodiesel at the plant and wholesale levels may reflect structural changes in the biomass-based diesel market that weakened the D4 RIN price link between biodiesel and ULSD. Under a binding RFS volume mandate, the BBD supply price is higher than the ULSD demand price, and the RIN value equals the difference between these two

[3] Notice that the grand total in tables 7 to 10 contains both geographic spillovers within each level of the supply chain and across levels. This complicates interpretation of dynamics and their causes.

prices (Gerveni and Irwin, 2025). As long as the mandate is binding, movements in ULSD prices are directly reflected to BBD prices through the RIN wedge.

By mid-2023, the combined output of renewable diesel and FAME biodiesel was approaching the upper bound of what existing RVOs could accommodate. This led to the so-called "RIN cliff," the point at which BBD production exceeds the RVO, D4 RIN prices fall sharply due to oversupply, and BBD prices and production profits drop as a result (Gerveni et al., 2023c). Hubbs and Irwin (2025a) document that this oversupply condition largely prevailed through the first half of 2025. In addition, the D4 RIN bank had grown to an unprecedented 3.0 billion gallons by 2024 — more than three times the prior peak recorded in 2016 (Hubbs and Irwin, 2025b) — reflecting the extent to which RIN generation had outpaced compliance obligations. With the D4 RIN prices falling due to the overproduction, the linkage between BBD and ULSD prices likely weakened.

Another factor that has possibly added to the sharp decline in connectedness post-2022 is the accumulation of unresolved small refinery exemption (SRE) petitions. Hubbs and Irwin (2025a) document that a backlog of nearly 200 pending SRE applications spanning multiple compliance years existed going into 2025, creating widespread uncertainty about the effective level of BBD demand and further weakening the role of D4 RINs as a price link between biodiesel and ULSD. The key factors driving the changes in price connectedness are examined in detail in Section 4.5.

4.5 Drivers of Price Connectedness

This section identifies key factors correlated with time-varying total price connectedness in B100 plant-level, B100 wholesale-level, and ULSD wholesale-level markets. We estimate separate regression models for each group, as different variables may affect price connectedness differently depending on fuel type and supply chain position. We consider the following set of fundamental and policy variables for B100 plant-level and B100 wholesale-level price dynamics, denoted as $\boldsymbol{x_A}$:

$\boldsymbol{x_A}$ = (biodiesel production, renewable diesel production, ULSD production, biodiesel net imports, soybean oil price, D4 RINs price).

Set $\boldsymbol{x_A}$ includes variables representing supply (biodiesel production), demand (net imports), input costs (soybean oil price), policy incentives (D4 RIN price), blending activities (ULSD production), and displacement effects (renewable diesel production). Biodiesel production involves a variety of input costs, with feedstock prices representing the largest share − typically accounting for around 70‑80% of total production costs (Haas et al., 2006; Carriquiry et al., 2014). Biodiesel can be produced from multiple feedstocks, including soybean oil, corn oil, tallow, used cooking oil, and canola oil, each contributing differently to its total production. Among these, soybean oil is the dominant feedstock, representing 55.4% of total B100 feedstock usage over 2011‑2023, with corn oil being the next largest at 11.1% (Gerveni et al., 2024). We therefore select soybean oil as the input cost variable for the B100 regression models. We do not include additional feedstock prices in the regression, as the prices of alternative feedstocks are highly correlated with soybean oil − reflecting that vegetable oils and animal fats compete in the same processing and rendering supply chains, with price differences driven primarily by transportation and processing cost differentials rather than independent demand fundamentals. For instance, tallow prices are correlated with soybean oil prices at r = 0.95 over our sample period, meaning that including additional feedstock prices would introduce multicollinearity without adding explanatory power.

Regarding biofuel policy incentives beyond D4 RINs, another relevant variable is the biodiesel blenders' tax credit (BTC). However, Irwin, McCormack, and Stock (2020) show analytically and empirically that observed D4 RIN prices are determined by the biodiesel-ULSD spread and the RIN price adjusts to reflect whether the BTC is in effect. Since our D4 RIN price variable already internalizes the BTC effect on market incentives, the inclusion of a separate BTC dummy is redundant in the regression.

For the ULSD wholesale-level model, we employ a modified set of factors tailored to ULSD market characteristics. The new set, $\boldsymbol{x_B}$, includes the same explanatory variables as $\boldsymbol{x_A}$, with two substitutions: WTI crude oil price replaces soybean oil price to reflect ULSD's primary feedstock cost, and ULSD net imports replace B100 net imports:

$\boldsymbol{x_B}$ = (biodiesel production, renewable diesel production, ULSD production, ULSD net imports, WTI crude oil price, D4 RINs price).

Production, import and export data are available from the EIA monthly and expressed in average thousand barrels per day. We calculate net imports = imports – exports. We pair these data with daily and weekly connectedness data by assigning the monthly values to each day and week within the month. Daily biodiesel (D4) RIN prices expressed in \$/RIN are obtained from OPIS. Daily WTI crude oil prices are obtained from EIA and expressed in \$/barrel. Daily soybean oil prices are available from Jacobsen and expressed in cents/lb.

We specify the regression for each of the three groups as:

$$S(H)_{wi} \; = \; \boldsymbol{x}'_{gwi}\boldsymbol{\delta} + e_i \text{ with } \; e_i \sim N(0, \sigma^2) \tag{9}$$

where $S(H)_{wi}$ is a measure of the total connectedness index from the rolling window *i* of width *w,* associated with one of the three market groups. In the model where $S(H)_{wi}$ is the time varying connectedness in B100 plant-level, $H = 10$-week forecast horizon and *w=52* week rolling window. When $S(H)_{wi}$ is the time varying connectedness in B100 wholesale-level or ULSD wholesale-level, $H = 50$-day forecast horizon and *w=260* day rolling window. The set of explanatory variables within each rolling window is $\boldsymbol{x}'_{gwi}$ where *g*=*A*,*B*. Finally, $\boldsymbol{\delta}$ measures the linear dependence between $\boldsymbol{x}'_{gwi}$ and $S(H)_{wi}$.

We force the regression through the origin since price connectedness would not exist if all the explanatory variables are zero. To address potential endogenity issues, all right-hand side variables are lagged one period. However, while lagging the explanatory variables one period reduces the risk of simultaneity bias, it may not fully eliminate endogeneity. Particularly when error terms are serially correlated, a lagged regressor may still be correlated with the disturbance term, leaving some residual endogeneity.The results should be interpreted in light of this caution. Given the rolling window nature of the connectedness measures, we use the average value of each explanatory variable within each rolling window, which results in the explanatory variables being measured as moving averages. To account for autocorrelation and heteroskedasticity in the error terms, we apply Newey and West (1987) robust standard errors. The number of autocorrelated residual lags used in computing the robust standard errors is set to the integer part of $T^{1/4}$, where T denotes the number of observations, (Greene 2012). [4] Tables 11 – 13 present both the regression parameter estimates and, to facilitate interpretation, the elasticities at the sample means.

[4] Specifically, the lag length is set to 5 for the B100 plant-level model (where $T = 538$) and to 7 for the ULSD and B100 wholesale-level models (where $T = 2{,}701$).

4.5.1 Total Connectedness in B100 Plant-Level Markets

Soybean oil price, the primary B100 feedstock, has the highest correlation with total market connectedness. A 100% increase in feedstock prices would boost total connectedness by 70.58% (Table 11), suggesting that production cost changes drive the strongest increases in information flows across markets. This aligns with previous literature findings that rising production costs often intensify price interconnectedness within related markets as they adjust to shared cost pressures (e.g., Kilian & Park, 2009; Serra & Zilberman, 2013). The next largest correlation is observed with biodiesel production, with an elasticity of 36.34%. This positive and statistically significant relationship suggests that increased domestic supply of biodiesel leads to tighter connections across B100 plant-level markets. With an elasticity of 1.39%, biodiesel net imports slightly enhance price interconnectedness within B100 plant-level markets, possibly by linking domestic regions to global pricing dynamics.

The coefficients for ULSD production, RINs D4 price and renewable diesel production are not statistically significant. The lack of correlation between ULSD production and B100 total connectedness at the plant level may stem from the fact that biodiesel blending with petroleum occurs at the wholesale level. Similarly, although D4 RINs prices are central policy instruments that incentivize biodiesel production, their price effects are not statistically significant at the plant level as compliance with blending mandates occurs at the wholesale level.

Renewable diesel's exponential growth since 2021 does not significantly influence connectedness across B100 plant-level markets for the period of analysis. It is possible that increased renewable diesel production, a substitute for both B100 and ULSD, is reflected through changes in B100 production. As renewable diesel production continues to rise and demand for B100 decreases, the B100 biodiesel markets may become thinner, reducing the degree of market integration.

4.5.2 Total Connectedness in B100 Wholesale Markets

Regression results in Table 12 show the key factors influencing total connectedness in B100 wholesale markets. Unlike plant-level markets where soybean oil and biodiesel production dominate, ULSD production emerges as the primary driver at the wholesale level with an elasticity of 71.31%. This substantially exceeds the influence of soybean oil (16.81%) and biodiesel production (15.63%), reflecting that B100 wholesale price shocks driven by changes in USLD production generate the strongest information flows across B100 wholesale markets. This finding highlights the central role of refining, blending and distribution in price formation.

Soybean oil ranks second in importance. As the primary biodiesel feedstock, soybean oil prices influence pricing dynamics throughout the supply chain. Biodiesel production follows closely with an elasticity of 15.63%, indicating that increased production continues to increase price connectedness at the wholesale level. Other positive contributors include biodiesel net imports and D4 RINs price, with elasticities of 0.77% and 1.36%, respectively. D4 RIN prices are an indicator of blending mandates cost of compliance. Higher D4 RINs prices incentivize refiners to blend more biodiesel (Gerveni et al., 2023), which strengthens price interactions among wholesale markets.

Renewable diesel production exhibits a statistically significant negative correlation with B100 wholesale price connectedness, with an elasticity of -3.18%, unlike its non-significant effect at the plant level. This suggests renewable diesel's role as a direct substitute for biodiesel manifests primarily at the distribution stage during our sample period. Its negative influence indicates that as renewable diesel production increases, price discovery centers move away from B100 markets, resulting in wholesale markets being less tied together. The different effects of ULSD production, D4 RINs prices, and renewable diesel production between wholesale and plant-level underscores the importance of examining connectedness across different nodes of the supply chain.

4.5.3 Total Connectedness in ULSD Wholesale Markets

Regression results in Table 13 reveal significant factors correlated with price connectedness in ULSD wholesale markets. This model uses the same explanatory variables as the B100 connectedness regressions, except that WTI crude oil price replaces soybean oil to reflect ULSD's primary feedstock cost, and ULSD net imports replace B100 net imports. ULSD production exhibits the highest correlation, with an elasticity of 153.79%. This suggests strong propagation of supply-related price shocks across ULSD wholesale markets. B100 production ranks second with an elasticity of 26.15%. As discussed, both ULSD and B100 production are positively correlated with B100 wholesale connectedness, with ULSD production exerting substantially stronger effects (Table 12). The larger role of ULSD production in both regressions relative to B100 production possibly reflects the blending structure. Because biodiesel typically constitutes

5-20% of blended diesel, both B100 and ULSD markets are more responsive to ULSD than B100 supply.

ULSD net imports show a statistically significant and positive correlation with ULSD wholesale price connectedness, with an elasticity of 13.23%. This mirrors the positive effect of net imports observed in B100 markets, suggesting an integrative role of international trade in domestic markets. D4 RINs price also displays a small but significant positive effect (0.84%). Its impact is similar to that observed in B100 wholesale connectedness (Table 12) and is consistent with renewable volume obligations compliance taking place at the wholesale supply chain level. Because B100 is blended into ULSD, policy incentives affecting the biodiesel wholesale market propagate through the petroleum diesel pricing system as well.

In contrast, WTI crude oil prices negatively correlate with ULSD wholesale connectedness, with an elasticity of -36.26%. This suggests feedstock price shocks are transferred less efficiently across ULSD domestic wholesale markets. As crude prices rise, some wholesale distributors may absorb portions of cost increases or pass them through at different rates depending on storage capacity or local demand elasticities, causing market prices to move less uniformly.

As in B100 wholesale markets, renewable diesel production negatively impacts connectedness in ULSD wholesale markets, with an elasticity of -3.54%. As a direct substitute for ULSD, increased renewable diesel production reduces petroleum diesel demand, weakening price interactions. This finding reflects the ongoing market transformation driven by renewable diesel, particularly in California, where over 80% of renewable diesel is consumed due to LCFS incentives (Gerveni et al., 2023). Its growing market share disrupts traditional price relationships by creating new regional supply patterns.

5. Conclusions

We quantify market integration between U.S. biodiesel (B100) plant-level markets, wholesale B100 markets, and petroleum diesel (ULSD) wholesale markets. We analyze price dynamics and interactions between these markets, revealing how biodiesel and conventional diesel markets are interlinked within and across their supply chains. We derive price connectedness following Diebold and Yilmaz (2012, 2014) from variance decompositions of the forecast errors from a Vector Autoregression (VAR) model capturing price linkages. We also explore the factors correlated with these connectedness measures to understand the drivers of price connectedness separately within each market group.

The analysis spans from January 4, 2013, to May 10, 2024, and incorporates key regional markets in the U.S. Results indicate strong price connectedness between plant and wholesale biodiesel markets and between B100 and ULSD wholesale markets, where more than 70% of the price forecast error variance stems from within and cross-market information flows. These high connectedness values reveal strong price transmission mechanisms within the biodiesel supply chain and between biodiesel and ULSD markets. Combined with the Johansen cointegration evidence confirming long-run equilibrium relationships within and across these markets, these results support the conclusion that biodiesel and petroleum diesel markets function as an integrated system rather than isolated segments.

The Gulf Coast emerges as the largest transmitter of information in both B100 and ULSD wholesale markets. This highlights its central role in refining and distribution for both biodiesel and petroleum diesel. The Upper Midwest plays a significant role in transmitting price connectedness at the B100 plant level, consistent with its position as the largest biodiesel production hub in the U.S. The West Coast is a net receiver of price information both at the plant and wholesale levels, reflecting its dependence on external supply chains and unique regulatory environment, such as California's Low Carbon Fuel Standard (LCFS).

Market fundamentals strongly drive price connectedness in biodiesel and ULSD markets. Changes in production exert the greatest influence, with ULSD production (with elasticities between 71.31% and 153.79%) generating the largest information spillovers between wholesale markets. Biodiesel production, with an elasticity of 36.34%, is the second largest driver of plant-level spillovers, following soybean oil price with an elasticity of 70.58. Net imports enhance connectedness through international trade linkages. Consistent with the current policy scheme, D4 RINs prices increase information flows only between wholesale markets. Most importantly, renewable diesel production, with elasticities ranging from -3.18 to -3.54%, reduces connectedness at wholesale levels by functioning as a direct substitute for both biodiesel and ULSD, fundamentally reshaping traditional market relationships and shifting price discovery hubs.

Our findings provide important insights for policymakers overseeing biodiesel and petroleum diesel markets. The high levels of connectedness between plant and wholesale biodiesel markets (78.50%) and between biodiesel and ULSD wholesale markets (72.30%) demonstrate that policy interventions targeting any segment of these markets will propagate throughout the entire supply chain. The varied roles of markets as net emitters and net receivers of information require policy approaches that anticipate cross-market impacts. Policymakers should particularly note regional differences in price transmission, with interventions in hub markets like the Gulf Coast and Upper Midwest likely to have broader impacts than those targeting more isolated regions like the West Coast.

The effectiveness of RIN price mechanisms in driving biodiesel prices is confirmed by their significant positive correlation with wholesale market integration, though their impact appears limited to the distribution level rather than production. The negative correlation between renewable diesel production and price connectedness in both biodiesel and ULSD wholesale markets represents more than a temporary adjustment—it signals a fundamental restructuring of traditional fuel markets. As renewable diesel production continues to grow, particularly in regions with supportive policies like California's LCFS, we expect further declines in market connectedness. Our results suggest this restructuring is weakening price linkages across traditional markets as price discovery shifts to reflect the new reality.

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Tables

Table 1. Regional Distribution of Annual U.S. Biodiesel Production and Consumption, 2022-2023

Region	Number of Biodiesel Plants		Biodiesel Nameplate Capacity (Million Gallons)		Biodiesel Production (Million Gallons)		Biodiesel Consumption (Million Gallons)	
Lower Midwest	7	(13%)	188	(9%)	148	(9%)	159	(10%)
Northeast	6	(11%)	112	(5%)	64	(4%)	174	(10%)
Rocky Mountains	0	(0%)	0	(0%)	0	(0%)	13	(1%)
South Central	7	(13%)	384	(18%)	297	(18%)	302	(18%)
Southeast	6	(11%)	95	(5%)	66	(4%)	130	(8%)
Upper Midwest	23	(42%)	1,120	(54%)	896	(55%)	456	(28%)
West Coast	6	(11%)	193	(9%)	150	(9%)	425	(26%)
Total US	55	(100%)	2,092	(100%)	1,622	(100%)	1,658	(100%)

Note: Nameplate Production Capacity measures the estimated annual production capacity of a biodiesel plant**.** The Number of Biodiesel Plants and Nameplate Capacity data are from 2023, whereas Biodiesel Production and Consumption data are from 2022. All data are from the EIA.

Table 2. Regional Distribution of Annual U.S. Petroleum Production and Consumption, 2022 - 2023

Region	Number of Petroleum Refining Complexes		Refinery Annual Operating Capacity (Billion Gallons)		Petroleum Total Consumption (Billion Gallons)	
Lower Midwest	9	(7%)	21	(8%)	8	(13%)
Northeast	7	(6%)	13	(5%)	10	(17%)
Rocky Mountains	15	(12%)	8	(3%)	3	(5%)
South Central	55	(43%)	153	(57%)	13	(21%)
Southeast	7	(6%)	11	(4%)	10	(16%)
Upper Midwest	8	(6%)	24	(9%)	8	(14%)
West Coast	26	(20%)	41	(15%)	8	(14%)
Total US	127	(100%)	271	(100%)	61	(100%)

Note: Refinery Annual Operating Capacity refers to Atmospheric Crude Oil Distillation Capacity in 2023. Petroleum Total Consumption represents Distillate Fuel Oil consumption, excluding biodiesel and renewable diesel in 2022. All data are from the EIA.

Table 3. Connectedness Table Example

	x_1	x_2	...	x_N	From Others	From others including own
x_1	$\tilde{\theta}_{11}(H)$	$\tilde{\theta}_{12}(H)$	...	$\tilde{\theta}_{1N}(H)$	$\sum_{j=1, j\neq 1}^{N} \tilde{\theta}_{1j}(H)$	$\sum_{j=1}^{N} \tilde{\theta}_{1j}(H)$
x_2	$\tilde{\theta}_{21}(H)$	$\tilde{\theta}_{22}(H)$	...	$\tilde{\theta}_{2N}(H)$	$\sum_{j=1, j\neq 2}^{N} \tilde{\theta}_{2j}(H)$	$\sum_{j=1}^{N} \tilde{\theta}_{2j}(H)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$
x_N	$\tilde{\theta}_{N1}(H)$	$\tilde{\theta}_{N2}(H)$	...	$\tilde{\theta}_{NN}(H)$	$\sum_{j=1, j\neq N}^{N} \tilde{\theta}_{Nj}(H)$	$\sum_{j=1}^{N} \tilde{\theta}_{Nj}(H)$
To others	$\sum_{i=1, i\neq 1}^{N} \tilde{\theta}_{i1}(H)$	$\sum_{i=1, i\neq 2}^{N} \tilde{\theta}_{i2}(H)$	...	$\sum_{i=1, i\neq N}^{N} \tilde{\theta}_{iN}(H)$		
To others including own	$\sum_{i=1}^{N} \tilde{\theta}_{i1}(H)$	$\sum_{i=1}^{N} \tilde{\theta}_{i2}(H)$	...	$\sum_{i=1}^{N} \tilde{\theta}_{iN}(H)$	$\frac{1}{N}\sum_{i,j=1, j\neq i}^{N} \tilde{\theta}_{ji}(H)$	

Note: This table illustrates connectedness measures from the Diebold and Yilmaz (2012, 2014) methodology. These measures are based on Forecast Error Variance Decompositions (FEVD) from Vector Autoregressive (VAR) models estimated for biodiesel prices (plant and wholesale levels) and for wholesale biodiesel and wholesale USLD prices.

Table 4. Descriptive Statistics for Biodiesel (B100) Prices at the Plant and Wholesale Level and Ultra Low Sulfur Diesel (ULSD) Prices at the Wholesale Level ($/gallon) for January 4, 2013 to May 10 2024

	Series	Observations	Mean	Std Error	Minimum	Maximum
B100 Plant Level	Lower Midwest	593	3.91	1.35	2.31	7.75
	Northeast	593	4.14	1.35	2.43	7.76
	South Central	593	3.86	1.34	2.22	7.62
	Southeast	593	3.91	1.38	2.23	7.80
	Upper Midwest	593	3.96	1.32	2.42	7.82
	West Coast	593	4.47	1.43	2.79	8.14
B100 Wholesale	Chicago	2,843	4.04	1.40	2.48	8.4
	New York	2,843	4.10	1.50	2.35	8.56
	Gulf Coast	2,843	4.02	1.45	2.31	8.36
ULSD Wholesale	Chicago	2,843	2.17	0.73	0.49	4.73
	New York	2,843	2.23	0.79	0.60	5.40
	Gulf Coast	2,843	2.15	0.74	0.54	4.55
	Los Angeles	2,843	2.24	0.75	0.57	4.62

Note: The table summarizes weekly B100 prices at the plant level and daily B100 and ULSD prices at the wholesale level in $/gallon.

Table 5. Augmented Dickey-Fuller Unit Root Test Results, January 4, 2013 to May 10, 2024

	Level	First Difference		
Variable	**t-Statistic**	**t-Statistic**	**Lags**	**I(d)**
Panel A: B100 Plant-Level (weekly)				
ln(Lower Midwest)	−1.4440	-14.1520^{***}	AIC	I(1)
ln(Northeast)	−1.4595	-15.1079^{***}	AIC	I(1)
ln(South Central)	−1.3969	-14.9840^{***}	AIC	I(1)
ln(Southeast)	−1.3807	-17.4229^{***}	AIC	I(1)
ln(Upper Midwest)	−1.4492	-14.7013^{***}	AIC	I(1)
ln(West Coast)	−1.1036	-14.2513^{***}	AIC	I(1)
Panel B: B100 Wholesale (daily)				
ln(Chicago B100)	−1.2141	-36.2354^{***}	AIC	I(1)
ln(NY B100)	−1.1931	-36.5170^{***}	AIC	I(1)
ln(Gulf Coast B100)	−1.2739	-37.0578^{***}	AIC	I(1)
Panel C: ULSD Wholesale (daily)				
ln(Chicago ULSD)	−2.4825	-35.9311^{***}	AIC	I(1)
ln(NY ULSD)	−1.9579	-36.8068^{***}	AIC	I(1)
ln(Gulf Coast ULSD)	−1.9911	-37.7497^{***}	AIC	I(1)
ln(LA ULSD)	−2.1577	-36.4206^{***}	AIC	I(1)

Notes: The null hypothesis is that the series has a unit root (non-stationary). The test includes an intercept. Lag length selected by AIC. *** denotes rejection at the 1% level. ADF critical values: −3.43 (1%), −2.86 (5%), −2.57 (10%), from MacKinnon (1996). Panel A uses weekly data; Panels B and C use daily data.

Table 6. Johansen Cointegration Test Results for January 4, 2013 to May 10, 2024

Null Hypothesis	Eigenvalue	Trace Statistic	0.05 Critical Value	Max-Eigen Statistic	0.05 Critical Value
Panel A: B100 Plant-Level (K = 6, weekly)					
None *	0.0883	169.69 **	102.14	54.24 **	40.30
At most 1 *	0.0759	115.46 **	76.07	46.30 **	34.40
At most 2 *	0.0522	69.15 **	53.12	31.48 **	28.14
At most 3 *	0.0386	37.67 **	34.91	23.09 **	22.00
At most 4	0.0219	14.58	19.96	12.98	15.67
At most 5	0.0027	1.60	9.24	1.60	9.24
Panel B: B100 Wholesale (K = 12, daily)					
None *	0.0081	43.49 **	34.91	22.92 **	22.00
At most 1 *	0.0068	20.57 **	19.96	19.19 **	15.67
At most 2	0.0005	1.37	9.24	1.37	9.24
Panel C: ULSD Wholesale (K = 15, daily)					
None *	0.0275	193.27 **	53.12	78.90 **	28.14
At most 1 *	0.0231	114.37 **	34.91	66.22 **	22.00
At most 2 *	0.0155	48.15 **	19.96	44.25 **	15.67
At most 3	0.0014	3.90	9.24	3.90	9.24
Panel D: Biodiesel Plant and Wholesale System (K = 4, weekly)					
None *	0.1603	370.47 **	202.92	102.91 **	57.42
At most 1 *	0.1158	267.56 **	165.58	72.50 **	52.00
At most 2 *	0.1104	195.05 **	131.70	68.94 **	46.45
At most 3 *	0.0680	126.12 **	102.14	41.46 **	40.30
At most 4 *	0.0520	84.66 **	76.07	31.45	34.40
At most 5 *	0.0387	53.21 **	53.12	23.23	28.14
At most 6	0.0261	29.98	34.91	15.55	22.00
At most 7	0.0217	14.43	19.96	12.90	15.67
At most 8	0.0026	1.53	9.24	1.53	9.24

Table 6. (continued)

Null Hypothesis	Eigenvalue	Trace Statistic	0.05 Critical Value	Max-Eigen Statistic	0.05 Critical Value
Panel E: Wholesale B100 and ULSD system (K = 14, daily)					
None *	0.0347	274.95 **	131.70	100.04 **	46.45
At most 1 *	0.0233	174.91 **	102.14	66.75 **	40.30
At most 2 *	0.0153	108.16 **	76.07	43.65 **	34.40
At most 3 *	0.0084	64.51 **	53.12	23.75	28.14
At most 4 *	0.0073	40.76 **	34.91	20.72	22.00
At most 5 *	0.0060	20.05 **	19.96	17.10 **	15.67
At most 6	0.0010	2.94	9.24	2.94	9.24

Notes: K denotes the lag order selected by AIC. * next to the hypothesis denotes rejection by the trace test at the 0.05 level. ** denotes the test statistic exceeds the 0.05 critical value. Critical values from MacKinnon-Haug-Michelis (1999). The Johansen specification includes a constant in the cointegrating equation and no deterministic trend. All series are in natural logarithms. Panels A and D use weekly data; Panels B, C, and E use daily data.

Table 7. Weekly Biodiesel Price Connectedness at the Regional Plant and Wholesale Levels for January 4, 2013 to May 10, 2024

		Transmitted by Plant-Level ($S_{i\leftarrow j}$)						Transmitted by Wholesale-Level ($S_{i\leftarrow j}$)			($S_{i\leftarrow \blacksquare}$)
		Lower Midwest	North East	South Central	South East	Upper Midwest	West Coast	Chicago	New York	Gulf Coast	From Others
Received by Plant-Level ($S_{j\leftarrow i}$)	Lower Midwest	16.86	11.39	12.79	11.35	14.48	6.45	8.69	9.28	8.71	83.14
	Northeast	13.70	17.85	10.95	12.23	15.11	12.05	5.72	6.51	5.87	82.14
	South Central	10.87	12.00	19.16	8.93	13.05	9.61	8.17	9.44	8.77	80.84
	Southeast	14.56	14.50	9.94	16.97	12.68	7.81	7.59	7.96	7.99	83.03
	Upper Midwest	14.13	12.95	12.27	10.45	18.86	10.15	6.73	7.40	7.05	81.13
	West Coast	9.97	15.95	11.15	10.31	15.43	24.11	4.02	4.86	4.21	75.90
Received by Wholesale-Level ($S_{j\leftarrow i}$)	Chicago	5.97	2.68	5.77	4.04	4.82	1.35	26.25	23.69	25.42	73.74
	New York	5.52	2.73	5.47	3.16	4.78	2.05	24.70	27.30	24.30	72.71
	Gulf Coast	5.50	2.64	5.86	4.25	4.75	1.39	25.61	23.52	26.49	73.52
	To others ($S_{\blacksquare\leftarrow j}$)	80.22	74.84	74.20	64.72	85.10	50.86	91.23	92.66	92.32	706.10
	To others including own	97.08	92.69	93.36	81.69	103.96	74.97	117.48	119.96	118.81	78.50%

Note: Rows measure the connectedness received by each market and columns present the connectedness transmitted by each market. 'From others' represents total connectedness received from all other markets. 'To others' represents total connectedness transmitted to all other markets. 'To others including own' includes self-connectedness. The bottom-right value (78.50%) in the total connectedness index. Connectedness measures use 10 weeks-forecast horizon Generalized FEVD based on a VAR(1) model of weekly B100 plant-level and wholesale prices.

Table 8. Weekly Biodiesel Price Net Connectedness at the Regional Plant and Wholesale Levels for January 4, 2013 to May 10, 2024

		Transmitted by Plant-Level						Transmitted by Wholesale-Level		
		Lower Midwest	North East	South Central	South East	Upper Midwest	West Coast	Chicago	New York	Gulf Coast
Received by Plant-Level	Lower Midwest	0.00	-2.31	1.92	-3.21	0.35	-3.52	2.72	3.76	3.21
	Northeast	2.31	0.00	-1.05	-2.27	2.16	-3.90	3.04	3.78	3.23
	South Central	-1.92	1.05	0.00	-1.01	0.78	-1.54	2.40	3.97	2.91
	Southeast	3.21	2.27	1.01	0.00	2.23	-2.50	3.55	4.80	3.74
	Upper Midwest	-0.35	-2.16	-0.78	-2.23	0.00	-5.28	1.91	2.62	2.30
	West Coast	3.52	3.90	1.54	2.50	5.28	0.00	2.67	2.81	2.82
Received by Wholesale-Level	Chicago	-2.72	-3.04	-2.40	-3.55	-1.91	-2.67	0.00	-1.01	-0.19
	New York	-3.76	-3.78	-3.97	-4.80	-2.62	-2.81	1.01	0.00	0.78
	Gulf Coast	-3.21	-3.23	-2.91	-3.74	-2.30	-2.82	0.19	-0.78	0.00
	Total ($S_{\blacksquare\leftarrow j} - S_{j\leftarrow\blacksquare}$)	-2.92	-7.30	-6.64	-18.31	3.97	-25.04	17.49	19.95	18.80

Note: Net connectedness values represent the difference between connectedness transmitted by market j (columns) to market i (rows) minus connectedness received by market i (rows) from market j (columns). Row totals show each market's total net connectedness to all other markets. Based on 10-week forecast horizon Generalized FEVD from a VAR(1) model of weekly B100 plant-level and wholesale prices.

Table 9. Daily Biodiesel (B100) and Ultra Low Sulfur Diesel (ULSD) Price Connectedness at the Wholesale Level for January 4, 2013 to May 10, 2024

		Transmitted by B100 ($S_{i\leftarrow j}$)			Transmitted by ULSD ($S_{i\leftarrow j}$)				($S_{i\leftarrow \blacksquare}$)
		Chicago	New York	Gulf Coast	Chicago	New York	Gulf Coast	Los Angeles	From Others
Received by B100 ($S_{j\leftarrow i}$)	Chicago	29.94	13.83	24.19	5.14	10.15	10.37	6.39	70.10
	New York	17.79	32.95	25.51	3.24	7.75	8.07	4.70	67.10
	Gulf Coast	23.06	20.30	27.42	4.34	9.43	9.66	5.79	72.60
Received by ULSD ($S_{j\leftarrow i}$)	Chicago	6.13	3.38	5.64	34.71	18.28	18.28	13.58	65.30
	New York	8.57	5.79	8.63	13.44	25.16	23.15	15.26	74.80
	Gulf Coast	8.72	5.90	8.72	13.39	23.14	25.15	14.98	74.90
	Los Angeles	6.86	4.51	6.78	12.56	19.10	19.05	31.14	68.90
	To others ($S_{\blacksquare\leftarrow j}$)	71.10	53.70	79.50	52.10	87.80	88.60	60.70	493.50
	To others including own	98.90	96.80	99.00	89.30	108.00	108.30	99.70	72.30%

Note: Rows show connectedness received; columns present connectedness transmitted. ‘From others’ captures total connectedness received from all other markets. ‘To others’ represents total connectedness transmitted to all other markets. ‘To others including own’ includes self-connectedness. The bottom-right value (72.30%) is the total connectedness index. Based on 50-day forecast horizon Generalized FEVD from a VAR(1) model of daily B100 and ULSD wholesale prices.

Table 10. Daily Biodiesel (B100) and Ultra Low Sulfur Diesel (ULSD) Price Net Connectedness at the Wholesale Level for January 4, 2013 to May 10, 2024

		Transmitted by B100			Transmitted by ULSD			
		Chicago	New York	Gulf Coast	Chicago	New York	Gulf Coast	Los Angeles
Received by B100	Chicago	0.00	-3.96	1.13	-0.99	1.58	1.65	-0.47
	New York	3.96	0.00	5.21	-0.14	1.96	2.17	0.19
	Gulf Coast	-1.13	-5.21	0.00	-1.30	0.80	0.94	-0.99
Received by ULSD	Chicago	0.99	0.14	1.30	0.00	4.84	4.89	1.02
	New York	-1.58	-1.96	-0.80	-4.84	0.00	0.01	-3.84
	Gulf Coast	-1.65	-2.17	-0.94	-4.89	-0.01	0.00	-4.07
	Los Angeles	0.47	-0.19	0.99	-1.02	3.84	4.07	0.00
	Total ($S_{\blacksquare \leftarrow j} - S_{j \leftarrow \blacksquare}$)	1.00	-13.40	6.90	-13.20	13.00	13.70	-8.20

Note: Net connectedness values represent the difference between connectedness transmitted by market j (columns) to market i (rows) minus connectedness received by market i (rows) from market j (columns). Row totals show each market's total net connectedness to all other markets. Based on 50-day forecast horizon Generalized FEVD from a VAR(1) model of daily B100 and ULSD wholesale prices.

Table 11. Regression Explaining Total Connectedness for Biodiesel (B100) at the Plant Level, for January 4, 2014 to May 10, 2024

	Parameter Estimates	Elasticity (in %)
Biodiesel Production	0.243***	36.34
	(0.030)	
Renewable Diesel Production	-0.008	-0.42
	(0.008)	
ULSD Production	-0.001	-7.44
	(0.002)	
Biodiesel Net Imports	0.086***	1.39
	(0.034)	
Soybean Oil Price	13.337***	70.58
	(1.842)	
RINs Price (D4)	1.430	0.41
	(1.518)	
Observations	538	
Corr $(y, \hat{y})^2$	0.865	

Note: The table presents the results of regressing the time-varying connectedness measures on a rolling window approach (each window has a size of 52 weeks) and the within-widow average of the lagged explanatory variables. The Newey-West standard errors are reported in parenthesis. We force the regression through the origin. Corr measures the squared correlation between actual and fitted variable. Statistical significance is denoted as *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 12. Regression Explaining Total Connectedness for Biodiesel (B100) at the Wholesale Market Level, for January 4, 2014 to May 10, 2024

	Parameter Estimates	Elasticity (in %)
Biodiesel Production	0.093***	15.63
	(0.013)	
Renewable Diesel Production	-0.048***	-3.18
	(0.004)	
ULSD Production	0.010***	71.31
	(0.001)	
Biodiesel Net Imports	0.042***	0.77
	(0.013)	
Soybean Oil Price	2.857***	16.81
	(1.035)	
RINs Price (D4)	4.308***	1.36
	(0.841)	
Observations	2701	
Corr $(y, \hat{y})^2$	0.519	

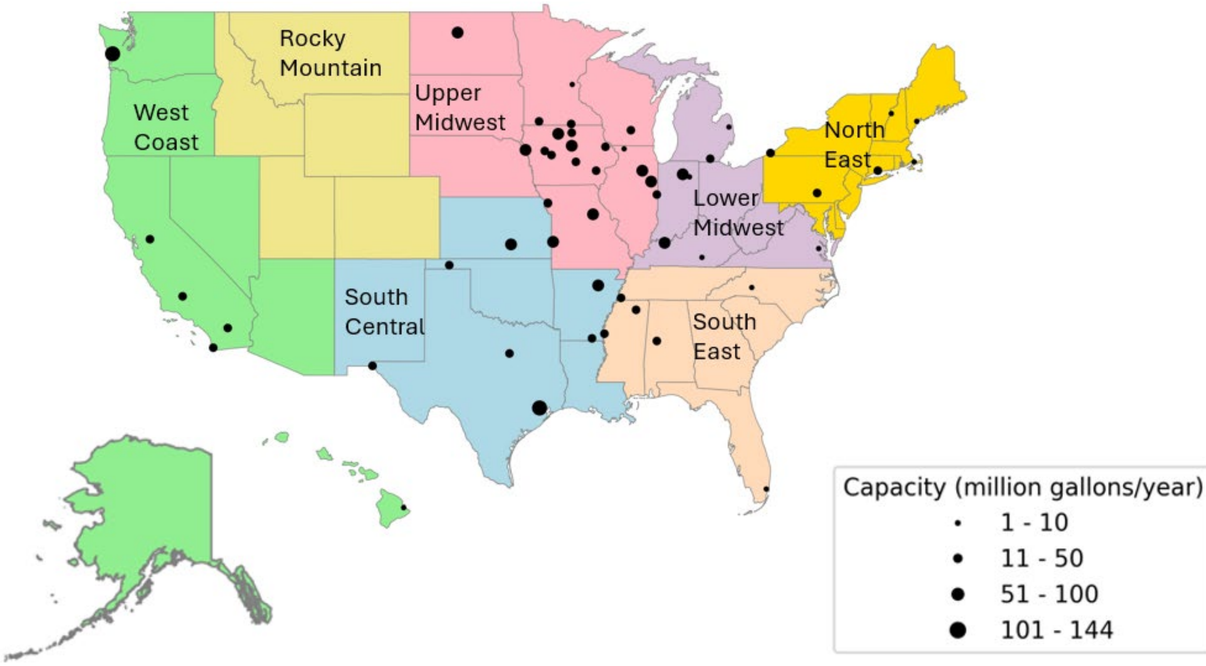
Note: The table presents the results of regressing the time-varying connectedness measures on a rolling window approach (each window has a size of 260 days) and the within-widow average of the lagged explanatory variables. The Newey-West standard errors are reported in parenthesis. We force the regression through the origin. Corr measures the squared correlation between actual and fitted variable. Statistical significance is denoted as *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13. Regression Explaining Total Connectedness for Ultra Low Sulfur Diesel (ULSD) at the Wholesale Market Level, for January 4, 2014 to May 10, 2024

	Parameter Estimates	Elasticity (in %)
Biodiesel Production	0.170***	26.15
	(0.013)	
Renewable Diesel Production	-0.076***	-3.54
	(0.007)	
ULSD Production	0.015***	153.79
	(0.001)	
ULSD Net Imports	0.006***	13.23
	(0.002)	
WTI Crude Oil Price	-2.989***	-36.26
	(0.604)	
RINs Price (D4)	3.127***	0.84
	(0.526)	
Observations	2701	
Corr $(y, \hat{y})^2$	0.687	

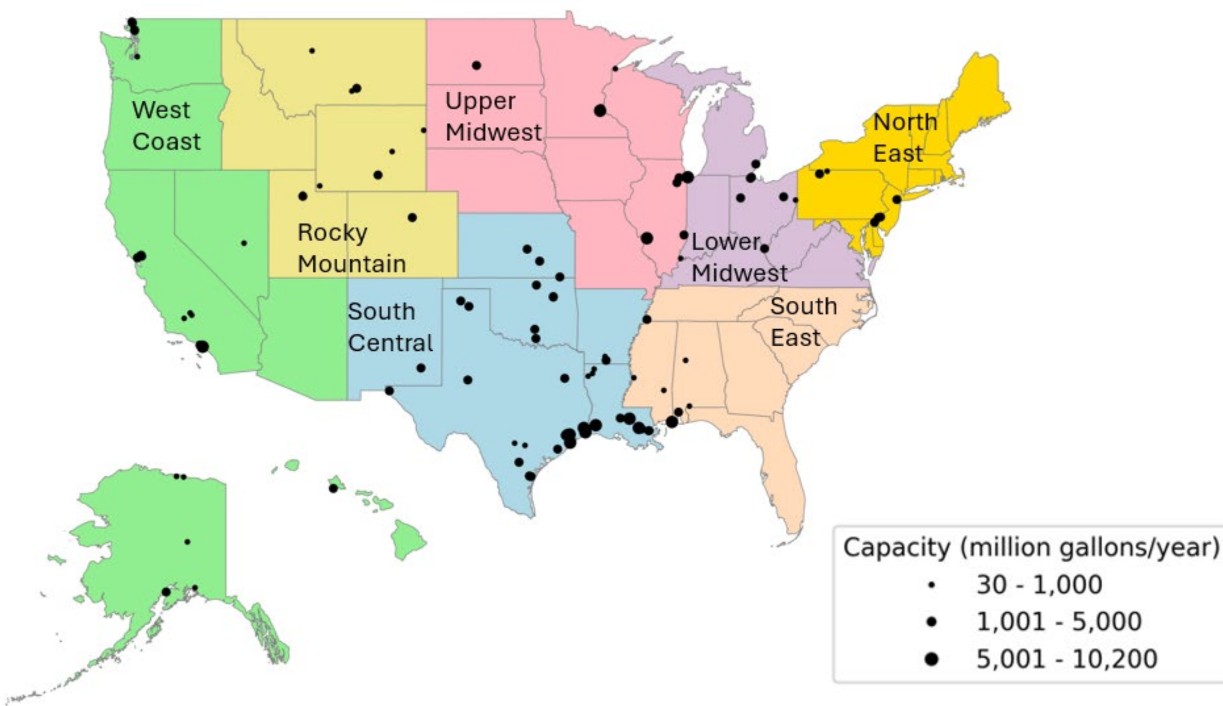
Note: The table presents the results of regressing the time-varying connectedness measures on a rolling window approach (each window has a size of 260 days) and the within-widow average of the lagged explanatory variables. The Newey-West standard errors are reported in parenthesis. We force the regression through the origin. Corr measures the squared correlation between actual and fitted variable. Statistical significance is denoted as *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figures



Source: EIA

Figure 1. Location of Biodiesel Plants



Source: EIA

Figure 2. Location of Petroleum Refining Complexes

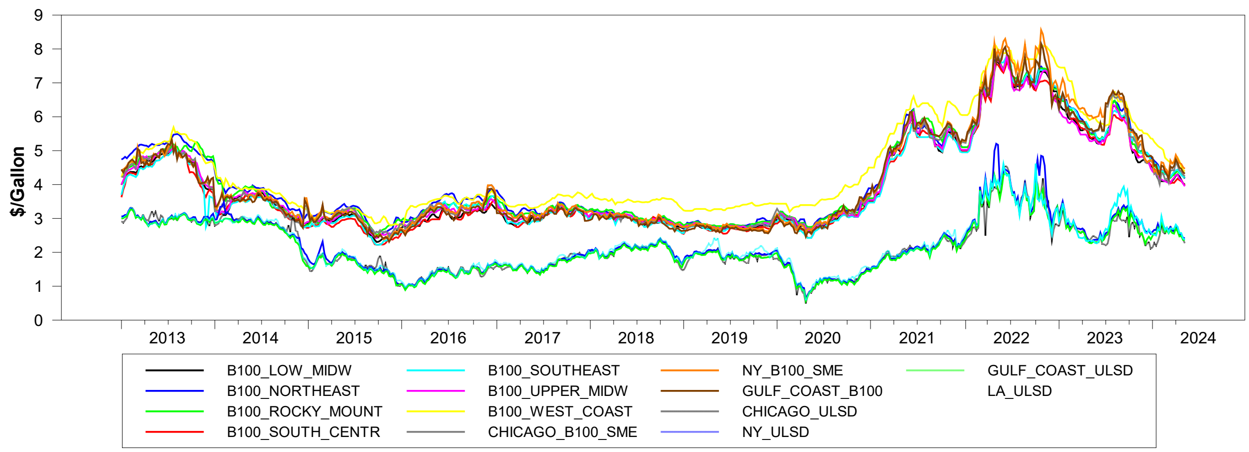
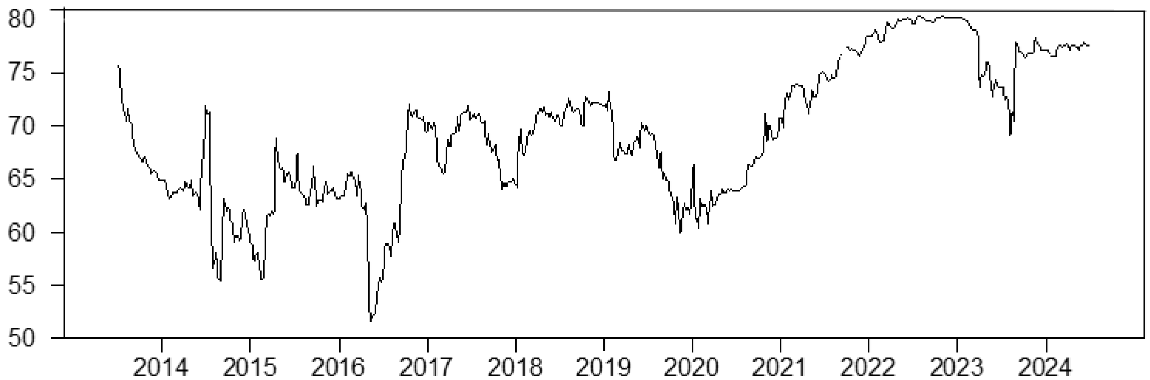


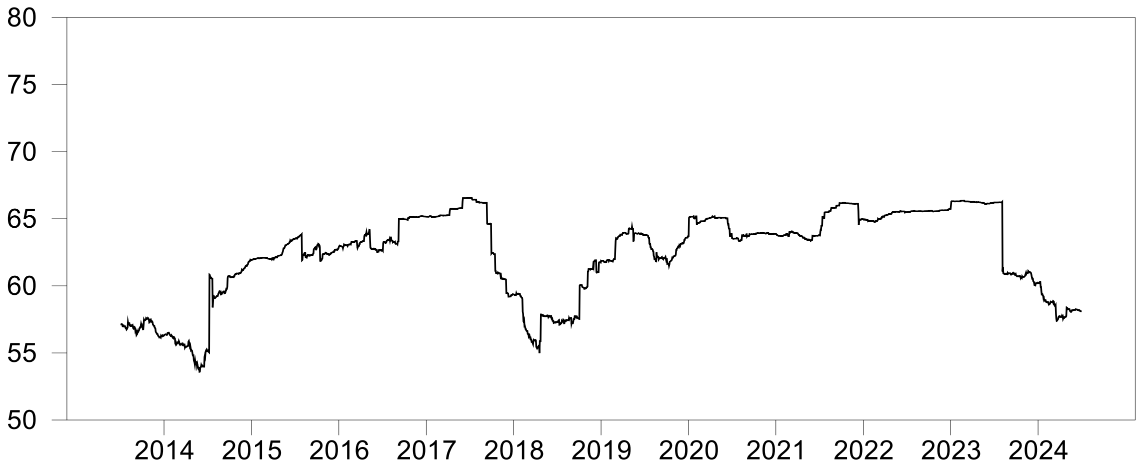
Figure 3. Weekly Biodiesel (B100) Prices at the Plant and Wholesale Level and Ultra Low Sulfur Diesel (ULSD) at the Wholesale Level, January 4, 2013 to May 10 2024

Note: Weekly spot prices ($/gallon) for B100 plant-level, B100 wholesale, and ULSD wholesale markets from January 4, 2013 to May 10, 2024. B100 plant-level prices from Fastmarkets; B100 and ULSD wholesale prices from Oil Price Information Service (OPIS).

a. Weekly Total Connectedness for Biodiesel (B100) at the Regional Plant Level



b. Daily Total Connectedness for Biodiesel (B100) at the Wholesale Level



c. Daily Total Connectedness for Ultra Low Sulfur Diesel (ULSD) at the Wholesale Level

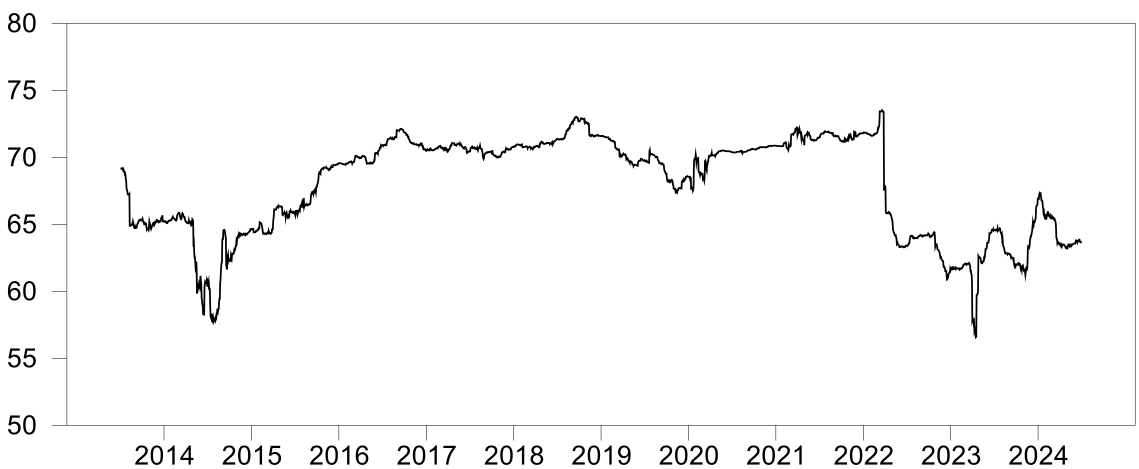


Figure 4. Dynamic Total Connectedness, for January 4, 2014 to May 10, 2024