Sticky Prices and Shifting Behaviour: Untangling Supply and Demand in U.S. Gasoline Markets

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Contents

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1 Executive Summary

1.1 Background

Gasoline remains one of the most consumed fuels in the United States and is the primary output of domestic oil refineries. According to the 2020 U.S. Census, approximately 92% of American households own at least one vehicle, underscoring the country's deeply ingrained car culture. Even with the surge in electric vehicle adoption, fully electric cars made up less than 10% of new vehicle sales in Q1 2025, which means that more than 9 out of 10 vehicles still rely on gasoline for at least part of their power.

However, the connection between routine driving and broader environmental issues such as climate change can often seem intangible. What tends to resonate more immediately with the public are fluctuations in gas prices. These prices are shaped by a variety of factors, including global supply and demand dynamics, crude oil benchmarks, refining and distribution costs, marketing expenses, and government-imposed taxes. Many of these elements are tracked by agencies such as the U.S. Energy Information Administration (EIA) and the Federal Reserve.

Gasoline prices also serve as a highly visible, albeit imperfect, indicator of broader economic conditions. Shifts at the pump can impact consumer sentiment and even correlate with political approval ratings. Low prices typically increase household purchasing power and reduce operational costs in key sectors such as transportation and manufacturing. However, while higher prices are burdensome, they can incentivize conservation and investments in sustainable energy alternatives. Regardless of price trends, companies along the fuel supply chain are responsible for their investors.

Given that car travel will continue to dominate U.S. transportation for the foreseeable future, understanding the behaviour of gasoline prices remains economically and politically significant.

1.2 Objectives

The primary objectives of this study are:

- Does gasoline demand (proxied by vehicle miles travelled) respond to changes in gasoline prices?
- How does gasoline supply (production levels) interact with prices? Is there evidence of supply-driven price shocks?
- Are there seasonal or structural shifts in these relationships over time (e.g., post-2008 or during COVID)?
- Is there a lead-lag dynamic between gasoline prices and stock returns?

1.3 Key Findings

- Clear negative correlation between gasoline supply and gasoline price

1.4 Recommendations

- placeholder

2 Technical Exposition

2.1 General Approach

This project investigates whether prices drive consumer behaviour or if demand and supply dynamics push prices - especially in light of sticky prices observed in administered markets. A two-pronged analytical framework was adopted: one focusing on the real economy (e.g., gasoline consumption and supply), and the other on financial market behaviour (e.g., stock returns across sectors exposed to oil prices). The approach taken in this study was to perform a comprehensive statistical analysis of historical data on gasoline supply, gasoline price, transportation statistics and equity returns across oil-sensitive firms and broader market indices to identify patterns in complex interactions between price, supply, consumer behaviour and stock returns. The analysis involved data collection and preprocessing, exploratory data analysis, and advanced statistical modelling techniques to test hypotheses and draw meaningful conclusions.

2.2 Theoretical Framework

Our analysis builds on the Keynesian concept of short-run price stickiness, which argues that gasoline prices adjust sluggishly to market shocks due to contractual rigidities, menu costs, and consumer expectations. In this framework, equilibrium is restored not through immediate price adjustments but through quantity-driven behavioural responses (e.g., reduced driving, adoption of fuel-efficient vehicles). This creates an asymmetric causal relationship: petrol price changes act as drivers of consumer behaviour, while reverse causality (behaviour driving prices) is insignificant in the short run.

However, real-world dynamics complicate this relationship:

- Supply shocks (e.g., OPEC+ production cuts, climate-related refinery disruptions) can trigger price volatility unrelated to contemporaneous demand
- Demand shocks (e.g., recession-driven commuting reductions or seasonal tourism spikes) may create feedback loops where behavioural changes indirectly affect prices through inventory adjustments or speculative futures trading

2.2.1 Hypotheses

To disentangle these dynamics, we test two competing claims:

- **Null Hypothesis (H_0):** Gasoline price fluctuations are primarily driven by shifts in demand (e.g., economic cycles) and supply (e.g., geopolitical disruptions), with no significant short-term feedback from prices to behaviour
- **Alternative Hypothesis (H_1):** Petrol price changes directly cause measurable behavioural adjustments (e.g., reduced vehicle miles travelled, modal shifts to public transit), consistent with sticky-price models

2.3 Data Collection and Cleaning

The data given by Correlation One underwent preprocessing to ensure data quality and compatibility: Each dataset was thoroughly examined for missing values, outliers, and inconsistencies. Missing data were handled using imputation or exclusion. Inconsistencies in data formatting and coding were resolved to ensure uniformity across datasets.

We utilised the following datasets to examine trends in gasoline pricing, supply-demand dynamics, transportation behaviour and stock prices. For each dataset, we identify specific variables of interest:

Dataset	**Selected Variable**	**Descriptions**
Weekly Gasoline Prices	Price	Gasoline prices reported for that week
Weekly Supply Estimates	Weekly U.S. Ending Stocks of Finished Motor Gasoline (Thousand Barrels)	Total production of conventional motor gasoline, defined as finished motor gasoline not included in the oxygenated or reformulated gasoline categories
Monthly Transport Statistics	Highway Vehicle Miles Travelled - All Systems	The Federal Highway Administration estimates vehicle miles travelled on all roads and streets in each month
Daily Stocks and Etfs	Close	Last price at which a stock trades at the end of the day

2.3.1 Variable: prices_weekly

We filter the dataset to focus exclusively on retail gasoline prices across all grades and formulations in the United States, and then we cleaned up the unneeded columns for clarity and ease of analysis.

1. Filter for gasoline price type
   - Keep only rows where 'Type' is 'All Grades All Formulations Retail Gasoline Prices (Dollars per Gallon)'
2. Filter geography
   - Keep only rows where 'Geography' is 'US'
3. Drop irrelevant columns
   - Remove 'Type', 'Type_Clean', and 'Unit' columns - these are now redundant

```python
# Filter for the relevant gasoline price type
prices = prices_weekly.copy()[prices_weekly['Type'] == 'All Grades All Formulations Retail Gasoline Prices  (Dollars per Gallon)']

# Keep only U.S. data
prices = prices[prices['Geography'] == 'US']

# Drop unnecessary columns
prices = prices.drop(columns=['Type', 'Type_Clean', 'Unit', 'Geography', 'Year']).reset_index(drop=True)

# Rename
prices = prices.rename(columns={
    'Date': 'date',
    'Year': 'year',
    'Price': 'price'
})
```
Python

Figure 1: Preprocessing and cleaning of weekly_gasoline_prices dataset

2.3.2 Variable: supply_weekly

Our rationale for using 'Weekly U.S Ending Stocks of Finished Motor Gasoline (Thousand Barrels)' as a proxy for supply and demand is because the variable represents the total inventory of conventional motor gasoline held in stock at the end of each week. This measure reflects the finished motor gasoline that is not included in oxygenate or reformulated gasoline categories, focusing solely on conventional gasoline production.

As such, it serves as a reliable proxy for gasoline supply for several reasons:

- Inventory Levels Represent Supply Availability: Ending stocks indicate how much gasoline is physically available in the market after production, imports, and consumption within the week
- Conventional Gasoline Focus: By isolating finished conventional motor gasoline, this measure avoids complications from alternative fuel blends, providing a clearer view of mainstream gasoline supply.
- Market Balancing Act: Changes in ending stocks reflect the balance between supply and demand; when stocks decline, it often signals higher consumer demand relative to production, and vice versa.

While this variable primarily measures supply, it also indirectly captures consumer demand dynamics:

- Demand Reduces Stocks: Higher consumption by consumers reduces the inventory of finished motor gasoline, causing ending stocks to fall.
- Supply-Demand Interaction: Thus, weekly fluctuations in ending stocks embody the net effect of production and consumer usage, making it a practical, observable proxy that links supply with real-time demand pressure in the market.

In summary, by tracking Weekly U.S. Ending Stocks of Finished Motor Gasoline, we capture a vital indicator of gasoline availability and consumption behaviour, enabling insightful analysis of supply-demand trends in the U.S. gasoline market.

2.3.3 Variable: transport

Vehicle miles travelled (VMT) can serve as a proxy for gasoline demand because the two are directly correlated: more miles driven typically require more gasoline consumption. Here's why this relationship is useful for analysing gasoline demand's response to price changes:

```python
supply = supply_weekly.copy()[['Date', 'Weekly U.S. Ending Stocks of Finished Motor Gasoline  (Thousand Barrels)']]
supply = supply.rename(columns={
    'Date': 'date',
    'Weekly U.S. Ending Stocks of Finished Motor Gasoline  (Thousand Barrels)': 'motor_gasoline_barrels'
})
```

Figure 2: Preprocessing and cleaning of weekly_supply_estimates dataset

- Direct Link Between VMT and Gasoline Demand: Gasoline demand is primarily driven by transportation use. If VMT increases, gasoline consumption generally rises, assuming fuel efficiency remains constant. This makes VMT a practical proxy for short-term gasoline demand, especially when detailed fuel sales data are unavailable.
- Price Elasticity of Demand: When gasoline prices rise, consumers often reduce driving (lowering VMT) to save costs. Conversely, lower prices may incentivise more driving. By analysing VMT alongside gasoline price data (e.g., "Highway Fuel Price - Regular Gasoline" in the dataset), we can estimate how sensitive demand is to price fluctuations.

By analysing how VMT fluctuates with gasoline prices in the dataset, while controlling for economic variables, we can infer the price elasticity of gasoline demand. This approach leverages VMT as a measurable, real-world indicator of consumption patterns, even if imperfect, to understand how consumers and businesses adjust behaviour in response to price changes.

```python
demand = transport_monthly.copy()[['Date', 'Highway Vehicle Miles Traveled - All Systems']].copy()
demand = demand.rename(columns={
    'Date': 'date',
    'Highway Vehicle Miles Traveled - All Systems': 'miles_travelled'
})
```

Figure 3: Preprocessing and cleaning of monthly_transportation_statistics

2.3.4 Variable: stock

We went with 'Close' as a proxy for the stock prices as it is the most commonly referenced price in financial markets and is widely accepted as the consensus value of a stock at the end of a trading day.

2.4 Exploratory Data Analysis

Before conducting formal statistical analyses, exploratory data analysis (EDA) was performed to gain insights into the data and identify potential patterns and relationships:

- **Descriptive Statistics:** Measures of central tendency and dispersion were calculated for key variables such as gasoline prices, gasoline supply and demand indicators. These statistics provided an overview of the data distribution and allowed for comparisons across states and time periods.
- **Temporal Trend Analysis:** Time series plots and correlation matrix were generated to examine temporal trends in demand, stock returns and gasoline prices over the available data period. These plots revealed potential changes in consumption patterns and gasoline and stock prices.

2.5 Statistical Analysis

2.5.1 Structural Break Analysis

To detect significant changes in trends and to potentially spot regular patterns, we performed structural break analysis across our selected variables.

Initially, we analysed for any structural breaks in gasoline price between 2018 to 2023 as shown in Figure 5. This analysis showed us that there were two main large structural breaks:

- 2021-03-29: Marks a significant shift due to post-COVID demand recovery, OPEC+ supply constraints, and fiscal stimulus in the U.S. These factors contributed to a sharp rise in crude oil and gasoline prices.
- 2022-02-07: Occurs shortly before the Russian invasion of Ukraine (Feb 24, 2022), likely reflecting market anticipation of geopolitical tensions and supply disruptions, leading to increased price volatility and a subsequent spike in fuel prices.

Furthermore, for Highway Vehicle Miles Travelled, a regular pattern of structural breaks was detected approximately every 5 weeks from January to November 2018 as shown in Figure 6. This likely reflects seasonal fluctuations in driving behaviour, including:

- Weather effects (e.g., fewer miles in winter, more in summer)
- Holiday-related travel spikes (e.g., Spring Break, Memorial Day, Labour Day)
- Economic consistency: No major economic shocks occurred in 2018, supporting the interpretation of cyclical, rather than structural, influences on demand.

Similarly, we noticed that structural breaks also occur at regular 5-week intervals across the entire period, from Jan 2018 to Nov 2022 in gasoline demand as shown in Figure 7.

This consistent timing suggests cyclical adjustments in gasoline supply, likely tied to:

- Seasonal demand patterns (e.g., summer driving season, holiday travel)
- Inventory management cycles by refineries and distributors
- Regulatory or reporting calendar effects (e.g., monthly or quarterly adjustments)

No abrupt structural shocks are evident, except:

- Early 2020 (Mar–May): aligns with COVID-19 onset, where sharp drops in mobility may have disrupted normal supply cycles.
- Early 2022: break around Feb 2022 may be linked to supply chain responses to Russia–Ukraine tensions.

Overall, the data reflects a highly regular, seasonal supply and demand pattern with notable disruptions during major global events.

2.5.2 Data Normalisation

By normalising our three selected variables we mentioned, we identified 4 key events between 2018 and 2023, as shown in Figure 8:

- Early 2020 Collapse (COVID-19 Onset)
  - Sharp simultaneous dip in price, demand, and supply around March–April 2020
  - Reflects global COVID-19 impact:
    - Demand (miles driven) plummeted
    - Prices fell sharply
    - Supply adjusted downward but with some lag
- Post-2020 Recovery
  - Demand recovers faster than supply and price, peaking in 2021
  - Prices start rising steadily through 2021 and into early 2022
  - Supply remains volatile, with a declining trend from 2021 onwards
- 2022 Price Spike
  - Prices peak around mid-2022, possibly due to global oil market shocks (e.g., Russia-Ukraine war).
  - Demand remains high, but supply continues to drop, suggesting supply constraints driving the price surge

- 2022–2023 Slowdown
  - All three variables decline into 2023, possibly due to inflation, policy tightening, or post-pandemic demand normalization

As a result we can draw these conclusions about the leading and lagging relationships:

Scenario	Observed?	Relationship 3	Evidence from plot	Supports (H_1)
Demand ↑ and Period ↑ in the same period	No (Not consistent)	Prices tend to lag demand	In 2021, normalized demand (blue) rises significantly ahead of the steep price (red) rise in 2022.	Yes
Price ↑ lags behind Demand ↑	Yes	Clear lag	Repeated pattern in mid-2020 to 2022: demand picks up before prices respond.	Yes
Supply ↓ and Price ↑ in the same period	Sometimes	Often simultaneous	In late 2021 and early 2022, supply (green) and price (red) move in opposite directions within the same time window, suggesting a contemporaneous supply shock.	Partially
Prices ↑ lag behind Supply ↓	Sometimes	Mild lag	In some intervals (e.g., late 2020), a drop in supply precedes a price rise, but timing is less consistent than with demand.	Yes (Weaker)

Table 1: Correlation analysis between demand, supply, and pricing patterns

2.5.3 Rolling Correlation Analysis

We look at the rolling correlation between stocks and gasoline prices. Selected stocks include, SPY (market wide index), CEO (Oil and Gas Equipment), EOG (Crude Petroleum and Natural Gas), SLB (Oil and Gas Field Services). Selected Gasoline includes the price difference between retail and crude oil, conventional US retail gasoline prices, and crude oil.

The graphs only depict correlations statistically significant to 5%.

Observations: Changes in the price difference between retail and crude oil is only correlated positively with changes in stock prices, where as changes in prices of conventional US retail Gasoline and crude oil correlate largely positively, but are sometimes negative. There is some seasonal variation observed, but this could also be volatility.

2.5.4 Cross-Correlation (Lead-Lag) Analysis

We conducted cross correlation to look into how the correlation differs with lags and we saw the following: The price difference between retail and crude oil, and crude oil prices have a significant correlations with lags of 1 or larger. The price of Conventional Retail Gasoline is correlated significantly with lag of 1.

1.

The relationship between gasoline demand and future prices was investigated using cross-correlation analysis, revealing critical insights into the temporal dynamics of price formation and market responsiveness. This analysis complements later findings on supply-price interactions, providing a comprehensive view of the forces shaping gasoline markets.

A moderate positive correlation (r=0.53) was observed between current demand levels and future gasoline prices, indicating that heightened demand is associated with subsequent price increases as shown in Figure 15. Cross-correlation function (CCF) analysis further refined this relationship, identifying a distinct peak at a 1-month lag (p=0.6), where demand leads price adjustments. The CCF exhibited a quadratic-like decay, with correlations diminishing symmetrically as the lag deviated from this central peak. This pattern suggests that demand shocks propagate into price changes rapidly, with the market largely absorbing these effects within a narrow temporal window.

Interpretation of Temporal Dynamics The lagged structure of the CCF implies a demand-driven price adjustment mechanism:

- Short-Term Responsiveness: The 1-month lag reflects the time required for suppliers to translate observed demand changes into price revisions. For instance, a surge in summer travel demand in June correlates strongly with July price increases, likely driven by anticipatory pricing strategies.
- Quadratic Decay: The symmetrical decline in correlation strength at lags beyond ± 1 month indicates that price adjustments occur swiftly and are not sustained over extended periods. This rapid dissipation aligns with the perishable nature of demand in volatile markets, where new information quickly supersedes past trends.

Practical implications:

- Forecasting Utility: The 1-month demand-price correlation provides a actionable lead time for price predictions. Firms could leverage near-term demand data to anticipate pricing trends, optimizing procurement and logistics.
- Policy Design: Regulators might target the 1-month adjustment window to implement demand-side interventions (e.g., temporary fuel subsidies during peak travel seasons), mitigating price volatility.

2.5.5 Granger Causality Tests

The investigation into the relationship between gasoline prices and supply reveals a temporal asymmetry that aligns with theories of price stickiness and delayed supply adjustments. Granger causality tests were employed to identify predictive relationships across varying time horizons, with results highlighting distinct short and longer term dynamics.

Short-Term Predictive Window (2-Month Lag) A statistically significant causal relationship emerges at a two-month lag (p=0.041), indicating that gasoline prices serve as a reliable predictor of near term supply adjustments. This short lag suggests that market participants respond operationally to price signals within a quarterly planning cycle. For instance, a sustained price increase is typically followed by measurable supply growth approximately two months later, likely reflecting inventory management decisions, short-term production scaling, or logistical re-allocations. These adjustments align with the concept of partial price stickiness, where prices transmit signals to suppliers, but operational constraints delay full supply responses.

Structural Indicators and Longer-Term Adjustments (3–4 Month Lags) The strongest predictive power occurs at a three-month lag (p=0.0096), with persistent effects extending to four months (p=0.034). This phase corresponds to structural supply-side changes, such as capacity investments or supply chain reconfigurations. The three-month lag likely captures the time required for firms to secure financing and coordinate with distributors, processes inherently delayed in markets with rigidities. These findings suggest that sustained price movements act as early warnings of systemic shifts: for example, a three-month trend of rising prices may signal impending supply shortages or capacity constraints, offering policymakers and firms a critical window for pre-emptive action.

Dissipation of Predictive Signals Beyond Four Months Lags exceeding four months show no statistical significance ($p>0.12$), implying that price signals lose predictive relevance over longer horizons. This decay aligns with the perishable nature of price information in volatile markets and reinforces the importance of shorter lags for actionable insights.

Implications for Price Stickiness and Market Functioning The asymmetry between price-to-supply causality (significant) and supply-to-price causality (insignificant) underscores the role of sticky prices in shaping supply dynamics. Suppliers appear to treat prices as semi-rigid signals, responding to lagged trends rather than real-time fluctuations. This behaviour may reflect institutional inertia, such as long-term contracts or regulatory frameworks that delay price pass-through. Meanwhile, the absence of supply-driven price effects suggests that supply shocks are either rapidly priced in or obscured by external factors (e.g., speculative demand, geopolitical events).

To assess the predictive relationships between gasoline prices and stock prices, we performed Granger causality tests across different lags. The results revealed distinct patterns by firm type and portfolio composition:

Short Lag Effects (∼1 week): Consists of companies with direct operational exposure to the oil sector, refiners (Valero Energy [VLO], Marathon Petroleum [MPC], Phillips 66 [PSX]), producers, and oilfield services companies. This suggests that they react quickly to changes in gasoline prices.

Longer Lag Effects (∼5 weeks): Other broader market indexes and diversified ETFs such as SPY, DIA, and VOO exhibited Granger causality with oil price series at longer lags. A lagged response may be indicative of indirect exposure, which may be caused by macroeconomic feedback loops or investor sentiment reacting to sustained movements in oil prices.

Refining Premium as a Predictor: For refiners, the refining margin (i.e., the difference between crude oil and retail gasoline prices) demonstrated greater predictive capability than gasoline prices in isolation. This emphasizes the significance of margin movements over input/output price levels in determining equity performance for refiners.

Retail Gasoline Price as a Broad Indicator: Retail gasoline prices were found to exhibit Granger causality with a wide group of firms, suggesting it acts as a proxy for the general consumer attitude and ability to spend. Its effect likely stems from its effect on disposable income and transportation cost, impacting consumer-facing businesses and logistics-based industries.

3 Discussion

3.1 Intersection of Consumer Behaviour and Stock Prices

The asymmetric response of equity markets to gasoline price fluctuations underscores the heterogeneous exposure of firms to energy dynamics. Refiners and oilfield service companies exhibited Granger causality at a 1-week lag, reflecting their direct operational reliance on gasoline margins. For instance, Valero Energy's stock price adjustments within days of margin shifts align with refiners' need to hedge crack spread volatility in futures markets. Conversely, broader indices like the S&P 500 responded at 5-week lags, suggesting indirect transmission through macroeconomic channels such as consumer spending or inflation expectations.

Retail gasoline prices emerged as a proxy for consumer sentiment, Granger-causing returns in logistics and consumer discretionary sectors. This linkage likely stems from gasoline's dual role as a cost input (e.g., for delivery firms) and a discretionary spending indicator (e.g., reduced driving lowers mall foot traffic). The superior predictive power of refining margins over absolute prices, particularly for energy equities—highlights the importance of margin analysis in sector-specific investing.

3.2 Policy recommendations

Based on the findings of this study, several policy recommendations can be proposed to address the complex issue of the volatile gasoline market:

1. Demand-Side Interventions:
   - Implement 1-month-ahead fuel subsidies during seasonal demand peaks (e.g., summer travel), leveraging the cross-correlation peak between demand and prices.

- Accelerate public transit incentives when prices exceed elasticity thresholds, using VMT data as a real-time consumption metric.

2. Supply-Side Stabilization:
   - Deploy strategic reserves during lag 0 supply shortfalls to exploit the -0.76 supply-price correlation.
   - Incentivise refinery investments during 3-month lagged price surges, aligning with Granger-causal supply responses.
3. Financial Market Oversight:
   - Mandate transparency in gasoline futures trading to curb speculation amplifying price volatility.
   - Incentivise refinery investments during 3-month lagged price surges, aligning with Granger-causal supply responses.

By implementing these policy recommendations, policymakers can take proactive steps to ad- dress the complex drivers of fluctuations in gasoline prices. These efforts require a multi-faceted approach that considers the interconnected nature both consumer behaviours and the stock market.

3.3 Limitations and Future Research Direction

While this study provides valuable insights into the impact of factors affecting gasoline prices, it is important to acknowledge its limitations and identify areas for future research.

Limitations:

- Unobserved confounders like geopolitical events or OPEC decisions may inflate observed correlations. Future studies could employ vector autoregression (VAR) models to isolate exogenous shocks.
- Aggregated U.S. data masks critical regional disparities (e.g., Gulf Coast refining vs. California regulations). Geographically stratified analyses could reveal localized arbitrage opportunities.
- Focus on large-cap equities overlooks small firms and private markets. Expanding to mid-cap energy stocks and logistics ETFs would enhance generalizability.

Future possible research directions:

- Investigate EV adoption thresholds where gasoline demand elasticity structurally shifts.
- Develop high-frequency inventory tracking using satellite imagery to refine supply proxies.
- Explore asymmetric price transmission mechanisms—whether demand responds more acutely to price surges than dips.

4 Conclusion

The analysis of gasoline price dynamics reveals a complex interplay between demand shocks, supply adjustments, and market rigidities. Through cross-correlation, Granger causality, and structural break analyses, this study identifies a cyclical feedback system where demand-driven price signals precede supply responses, which in turn moderate future price trajectories. These findings underscore the asymmetric and time-dependent nature of gasoline market adjustments, offering critical insights for stakeholders navigating this volatile sector.

Key Insights:

Demand as a Leading Indicator: The 1-month lag between demand surges and price increases highlights the market's rapid absorption of consumption trends. Consumers' driving behaviour, proxied by vehicle miles travelled, acts as a reliable predictor of near-term price movements, with correlations decaying symmetrically beyond this window. This rapid adjustment aligns with the perishable nature of demand signals in energy markets, where new data quickly eclipses past trends.

Supply's Dual Role: Supply levels exhibit a strong contemporaneous inverse relationship with prices (r=-0.76), reflecting real-time market clearing. However, Granger causality tests reveal delayed supply responses to price signals at 2-4 month lags, indicating that suppliers adjust production and inventories based on historical price trends rather than instantaneous fluctuations. This lagged response exemplifies the rigidities inherent in refinery operations, contractual obligations, and logistical constraints.

Structural Shocks and Cyclicality: Structural breaks identified during the COVID-19 pandemic and the Russia-Ukraine conflict demonstrate how exogenous shocks disrupt normal market cycles. Conversely, recurring breaks in miles travelled and supply data at 5-week intervals underscore the persistent seasonality and inventory management rhythms governing gasoline markets. These cyclical patterns mirror commodity "hog cycles," where price signals incentivize delayed supply corrections, perpetuating oscillations in supply.

Equity Market Linkages: The asymmetric response of sector-specific stocks to price changes—refiners react within 1 week, while broader indices respond at 5-week lags—emphasizes the heterogeneous exposure of firms to gasoline dynamics. Refining margins, rather than absolute price levels, prove most predictive of equity performance for oil-sensitive companies, highlighting the importance of margin analysis in financial decision-making.

Implications for Stakeholders

Policymakers: Strategic reserves should be deployed during contemporaneous supply shortfalls (lag 0) to stabilize prices, while lagged price trends (3–4 months) offer early warnings of structural deficits requiring long-term infrastructure investments.

Industry: Firms should align procurement with 1-month demand-price correlations and use 3-month-ahead price forecasts to optimize production schedules, balancing agility with the inertia of supply chains.

Investors: The inverse supply-price correlation (r=-0.76) supports hedging strategies, such as shorting futures during supply gluts. Refiners' sensitivity to margin fluctuations warrants focused attention on crack spread dynamics.

While this study elucidates critical temporal relationships, several limitations warrant consideration. Endogeneity risks, such as confounding effects from crude oil prices or regulatory shifts—may inflate observed correlations. Additionally, non-linear responses to extreme supply shocks (e.g., ¿20% disruptions) and regional variability in globalized markets necessitate further threshold and geospatial analyses. Future research could employ vector autoregression (VAR) models to isolate exogenous factors or explore asymmetric demand elasticity during price surges versus declines.

Gasoline markets epitomize a dynamic equilibrium where demand shocks, price stickiness, and supply rigidities interact across staggered time horizons. The 1-month demand-price lag and 3-month supply-response delay create a rhythmic interplay of cause and effect, demanding temporally stratified strategies from stakeholders. For policymakers, this implies tiered interventions: rapid responses to contemporaneous supply shocks and pre-emptive measures based on lagged price signals. For industry and investors, it necessitates dual focus on high-frequency demand data and medium-term supply trends.

Ultimately, this analysis reaffirms gasoline prices as both a reflection of immediate market pressures and a beacon for future supply adjustments. In an era of energy transition, where electric vehicles and sustainability mandates loom, understanding these temporal dynamics remains vital for managing the twilight years of gasoline's dominance in transportation. The lessons drawn here—of cyclicality, lagged responses, and asymmetric causality offer a blueprint for navigating not just gasoline markets, but all commodity systems where time horizons dictate economic outcomes.

5 References

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Methodology for Gasoline and Diesel Fuel Pump Components, Monthly Gasoline Makeup Percentages

Alpha Vantage and Yahoo! Finance, Energy Sector Stocks and Commodities (HLOC)

U.S. Dept of Transportation - Bureau of Transportation Statistics

6 Appendices

6.1 Appendix 1: Advanced Statistical Analysis Plots

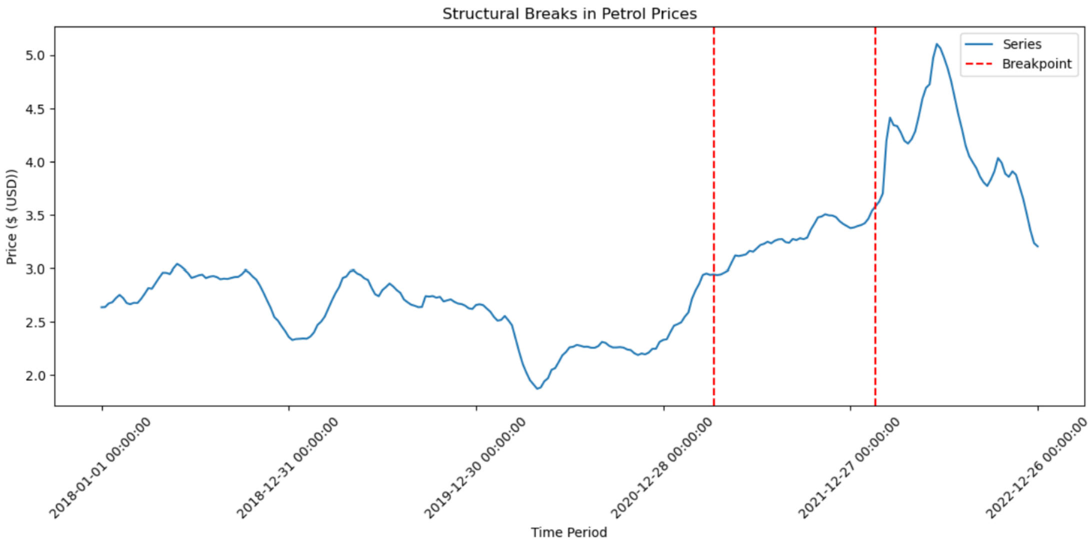

Figure 4: Plot showing two structural breaks in Gasoline Prices

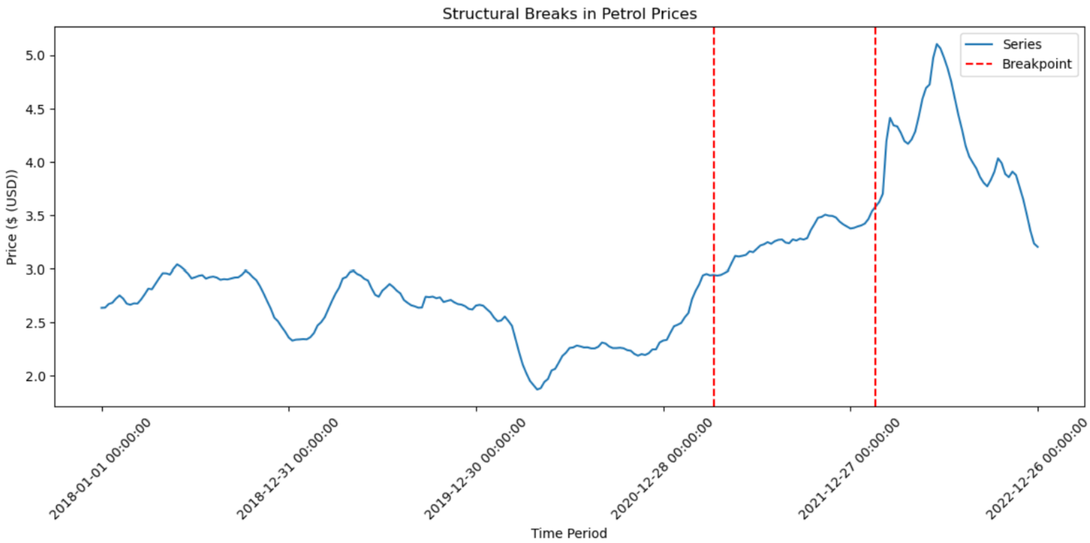

Figure 5: Plot showing two structural breaks in Gasoline Prices

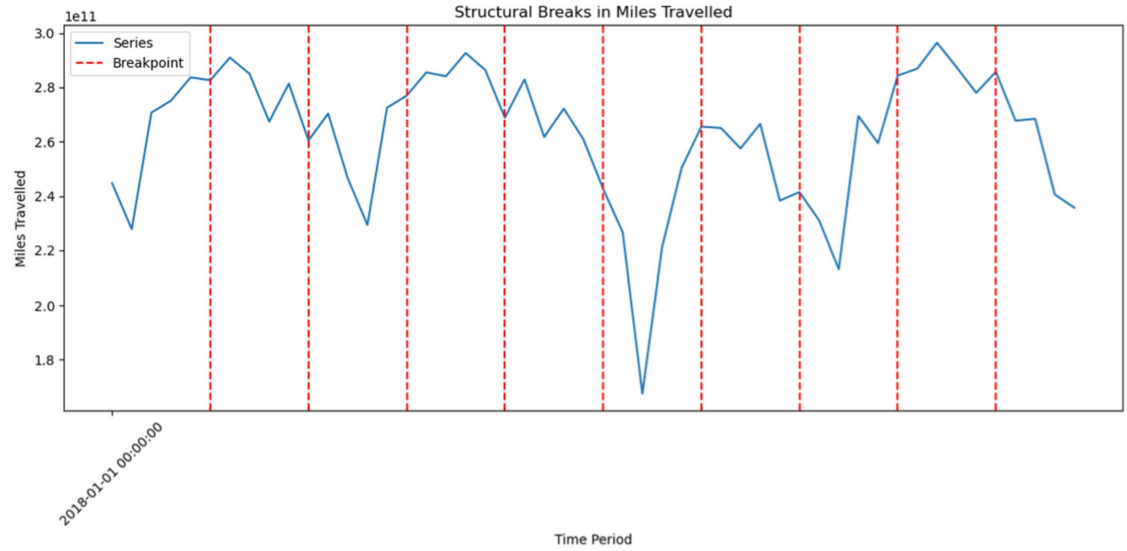

Figure 6: Plot showing two structural breaks in Gasoline Prices

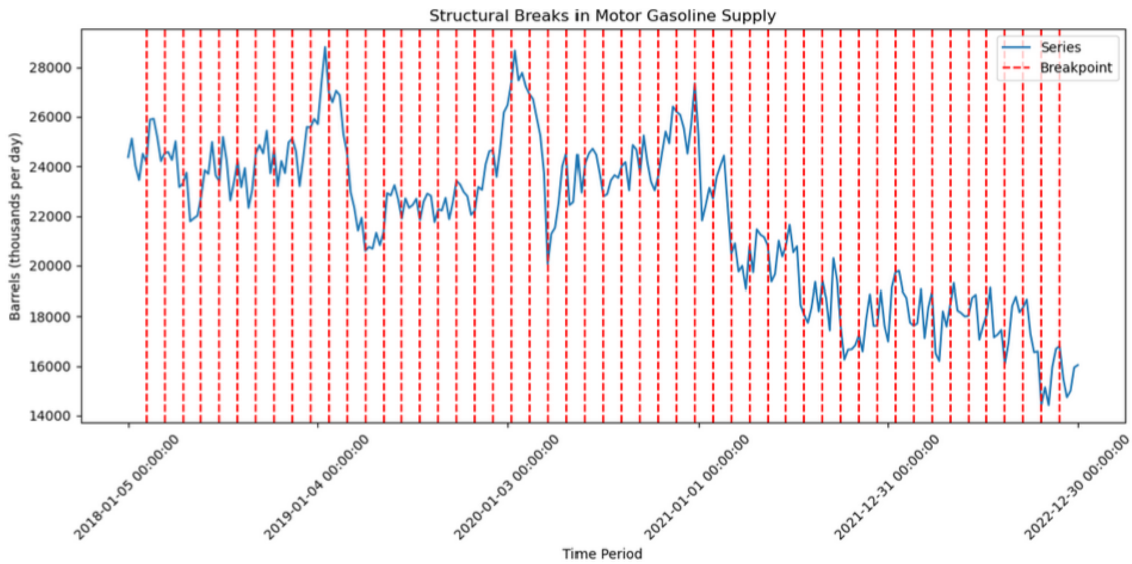

Figure 7: Plot showing two structural breaks in Gasoline Prices

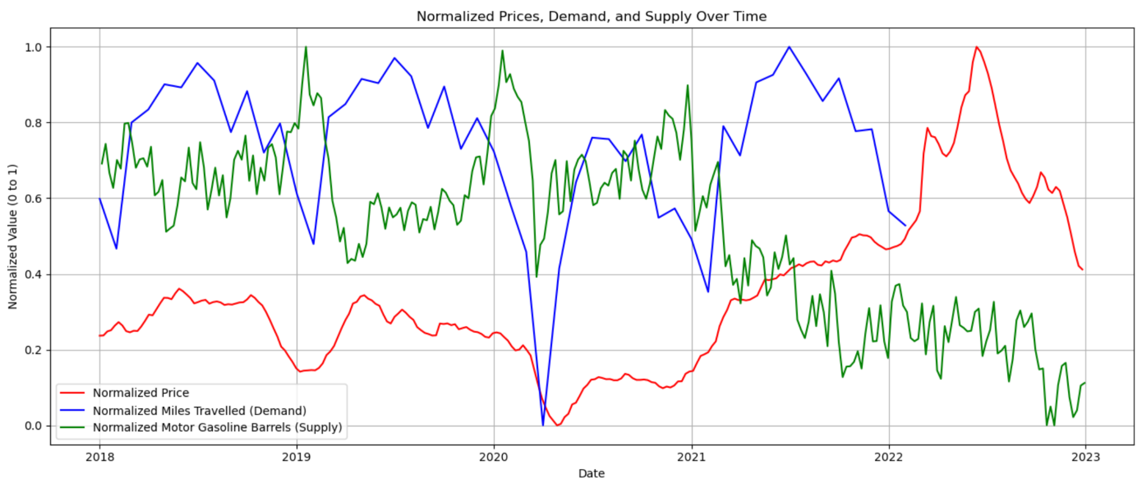

Figure 8: Plot of normalised data for 2018-2023

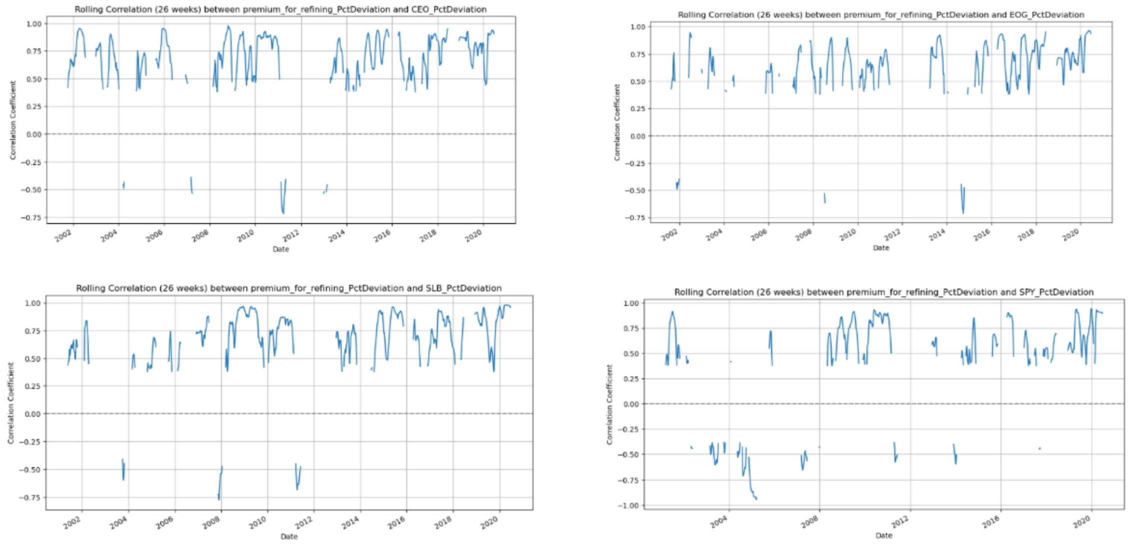

Figure 9: Correlation of Selected Stocks against price difference between retail and crude oil

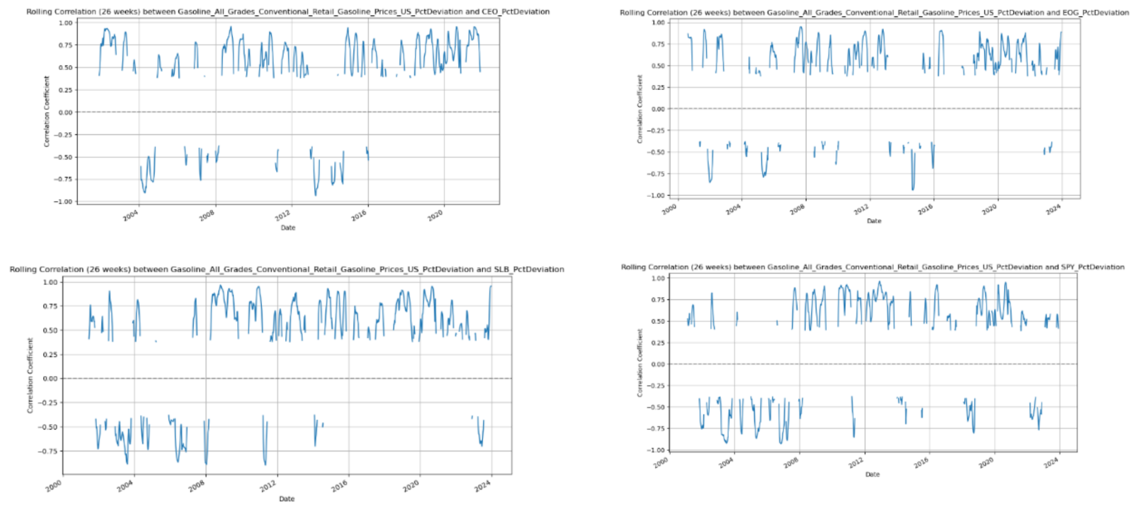

Figure 10: Correlation of Selected Stocks against retail gasoline prices

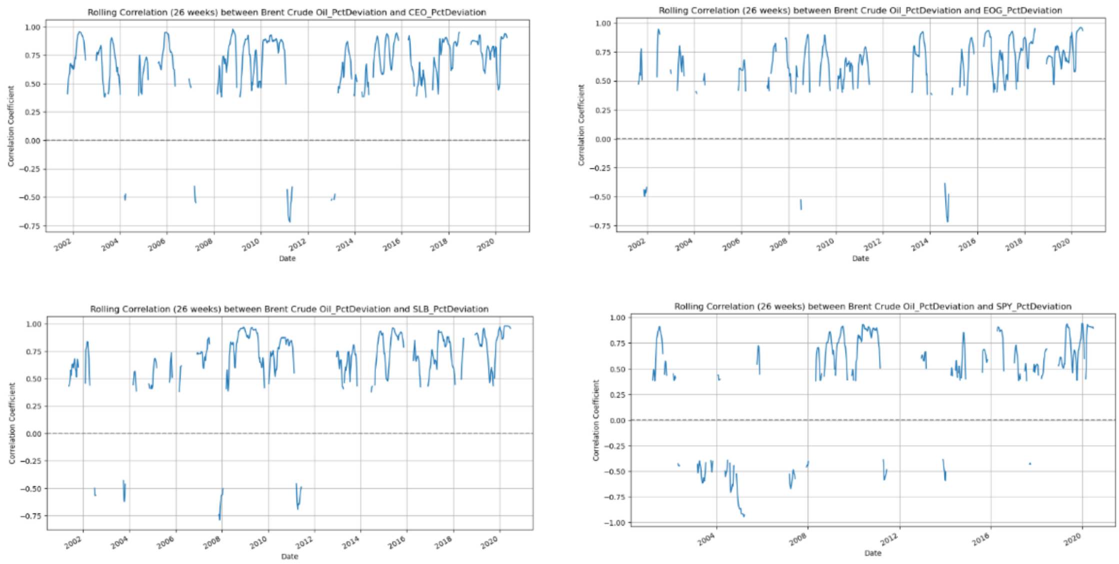

Figure 11: Correlation of Selected Stocks against crude oil

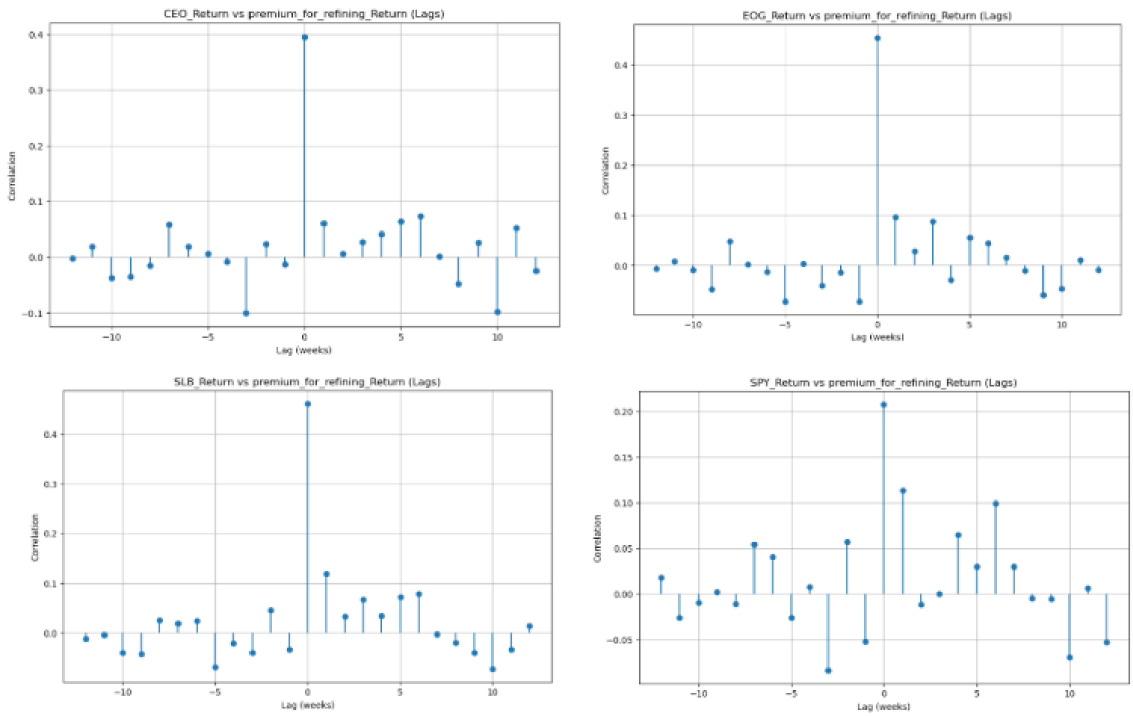

Figure 12: Correlation of Selected Stocks against price difference between retail and crude oil

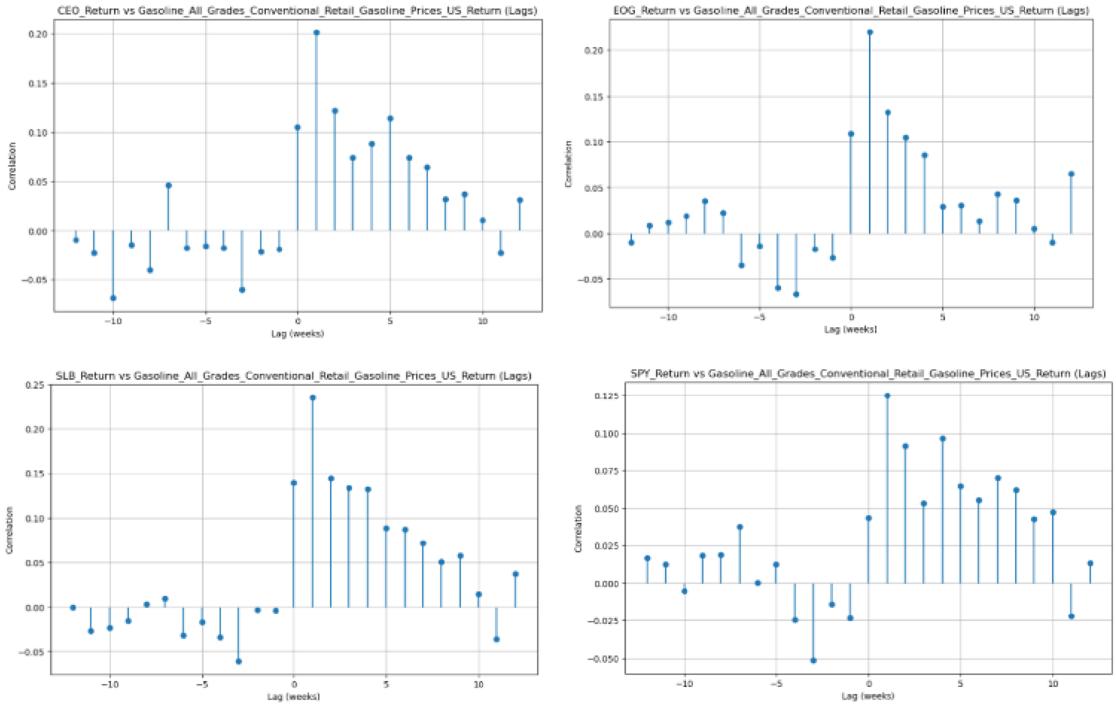

Figure 13: Correlation of Selected Stocks against retail gasoline prices

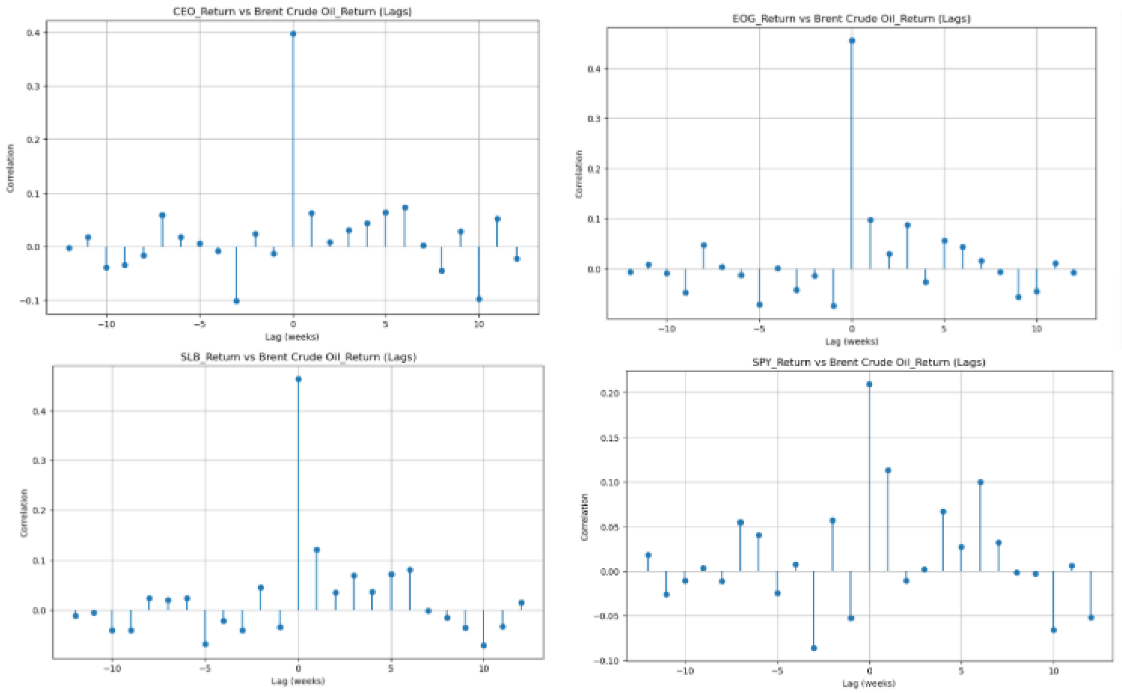

Figure 14: Correlation of Selected Stocks against crude oil

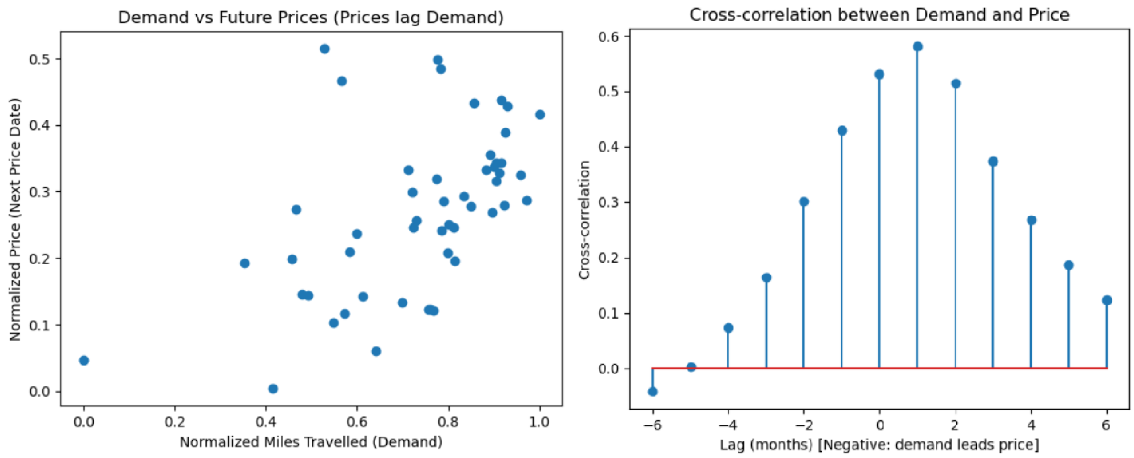

Figure 15: Correlation of Demand against Future Gasoline Prices (correlation of 0.53)

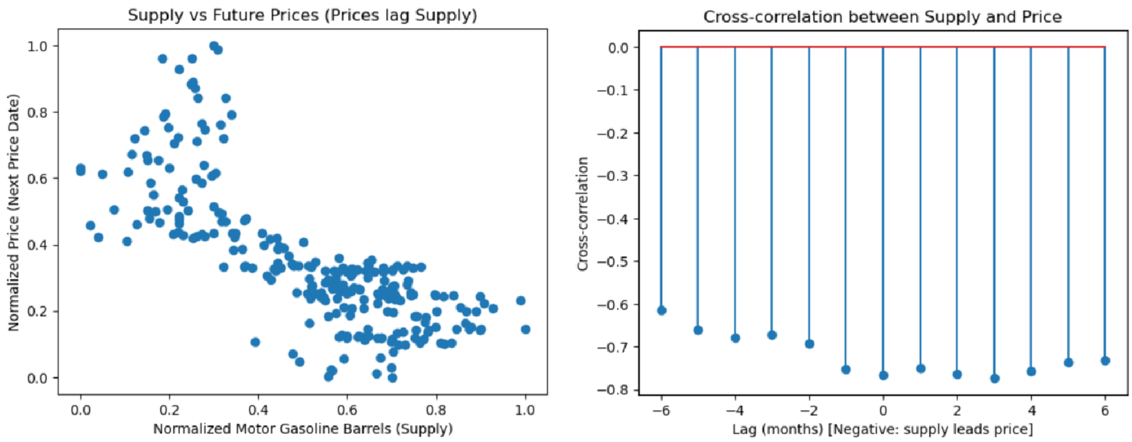

Figure 16: Correlation of Supply against Future Gasoline Prices (correlation of -0.76)

6.2 Appendix 2: Advanced Statistical Analysis Code

In [7]:

```python
# Drop NaNs in 'miles_travelled' and work on a copy to avoid SettingWithCopyWarning
demand = demand.dropna(subset=['miles_travelled']).copy()

# Convert 'date' to datetime
demand['date'] = pd.to_datetime(demand['date'], format='%m/%d/%Y %I:%M:%S %p', errors='coerce')

# Drop rows where datetime conversion failed
demand = demand.dropna(subset=['date'])

# Get min and max dates
start_date = demand['date'].min()
end_date = demand['date'].max()
start_date_str = start_date.strftime('%Y-%m-%d')
end_date_str = end_date.strftime('%Y-%m-%d')

print(f"Date range of demand: {start_date_str} to {end_date_str}")

# Format date column to "YYYY-MM-DD"
demand['date'] = demand['date'].dt.strftime('%Y-%m-%d')

# Reset index
demand = demand.reset_index(drop=True)
```

```
Date range of demand: 2018-01-01 to 2022-02-01
```

In [8]:

```python
# Ensure date columns are in datetime format
prices['date'] = pd.to_datetime(prices['date'])
demand['date'] = pd.to_datetime(demand['date'])
supply['date'] = pd.to_datetime(supply['date'])
```

In [9]:

```python
# Define date range
start_date = '2018-01-01'
end_date = '2022-12-31'

# Filter both DataFrames by the date range
prices = prices[(prices['date'] >= start_date) & (prices['date'] <= end_date)].reset_index(drop=True)
supply = supply[(supply['date'] >= start_date) & (supply['date'] <= end_date)].reset_index(drop=True)
```

Figure 17: Code to preprocess data

In [10]:

```python
def normalize(series):
    return (series - series.min()) / (series.max() - series.min())

# Apply normalization
prices['price_norm'] = normalize(prices['price'])
demand['miles_travelled_norm'] = normalize(demand['miles_travelled'])
supply['motor_gasoline_barrels_norm'] = normalize(supply['motor_gasoline_barrels'])

plt.figure(figsize=(14, 6))

plt.plot(prices['date'], prices['price_norm'], label='Normalized Price', color='red')
plt.plot(demand['date'], demand['miles_travelled_norm'], label='Normalized Miles Travelled (Demand)', color='blue')
plt.plot(supply['date'], supply['motor_gasoline_barrels_norm'], label='Normalized Motor Gasoline Barrels (Supply)', color='g

plt.xlabel('Date')
plt.ylabel('Normalized Value (0 to 1)')
plt.title('Normalized Prices, Demand, and Supply Over Time')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

Figure 18: Code to normalise data

In [12]:

```python
def structural_break(column, title, xlabel="Index", ylabel="Value", date_column=None, penalty=10):
    # 1. Extract the time series (1D or multivariate)
    series = column.values

    # 2. Choose the model and algorithm
    algo = rpt.Pelt(model="l2").fit(series)

    # 3. Select penalty
    try:
        breakpoints = algo.predict(pen=penalty)
    except rpt.exceptions.BadSegmentationParameters:
        print("Segmentation failed: not enough data or invalid parameters.")
        return

    # 4. Plot results with breakpoints
    # Manual plotting
    fig, ax = plt.subplots(figsize=(12, 6))
    ax.plot(series, label="Series")

    for bp in breakpoints[:-1]:  # Ignore last point (end of series)
        ax.axvline(bp, color="red", linestyle="--", label="Breakpoint" if bp == breakpoints[0] else "")

    ax.set_title(title)
    ax.set_xlabel(xlabel)
    ax.set_ylabel(ylabel)

    if date_column is not None:
        ax.set_xticks(range(0, len(date_column), 52))
        ax.set_xticklabels(date_column[::52], rotation=45)

    plt.legend()
    plt.tight_layout()
    plt.show()

    # 5. Print break dates (ignore last point which is end of series)
    if date_column is not None:
        valid_indices = [b - 1 for b in breakpoints[:-1] if 0 <= b - 1 < len(date_column)]
        break_dates = date_column.iloc[valid_indices]
        print("Detected break dates:")
        print(break_dates)
    else:
        print("Detected break indices:")
        print(breakpoints[:-1])
```

Figure 19: Code for performing structural analysis

Aligning the dates to test if price lags demand

In [18]:

```python
dates_right):
 find the closest date in right that is >= left date


ight[dates_right >= d]
pty:
append(candidates.min())

append(pd.NaT)


mand dates
after(demand['date'], prices['date'])

d and matched prices
y()
ce_date'] = matched_price_dates

hed price dates
ce_df.merge(prices[['date','price_norm']], left_on='matched_price_date', right_on='date', how='left', suffixes=('','_price'))

 price date
ce_df.dropna(subset=['price_norm'])
```

Correlation of demand vs future prices

In [19]:

```python
plt.scatter(demand_price_df['miles_travelled_norm'], demand_price_df['price_norm'])
plt.xlabel('Normalized Miles Travelled (Demand)')
plt.ylabel('Normalized Price (Next Price Date)')
plt.title('Demand vs Future Prices (Prices lag Demand)')
plt.show()

print('Correlation:', demand_price_df[['miles_travelled_norm','price_norm']].corr().iloc[0,1])
```

Figure 20: Code showing preprocessing of date and correlation analysis