THE IMPACT OF ATLANTIC SEASON TROPICAL DISTURBANCES ON TRANSPORTATION FUEL PRICES

MGT 6203 Group Project: Team 49

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Contents

Graphics and Figures

Tables

Objective

Background Information

Nearly half of all crude oil refining capacity in the United States lies in a 500-mile stretch along the United States Gulf Coast (USGC) [**Figure 1**]. This area experiences frequent tropical disturbances during the Atlantic hurricane season,[1] which can disrupt transportation fuel (gasoline, diesel, and jet fuel) production from refineries, as well as crude oil and natural gas production from the Gulf of Mexico and coastal waters. The price of transportation fuel is a key supply chain cost to many industries and can fluctuate based on a variety of factors, including feedstock prices, macroeconomic changes, geopolitics, and weather disruptions.

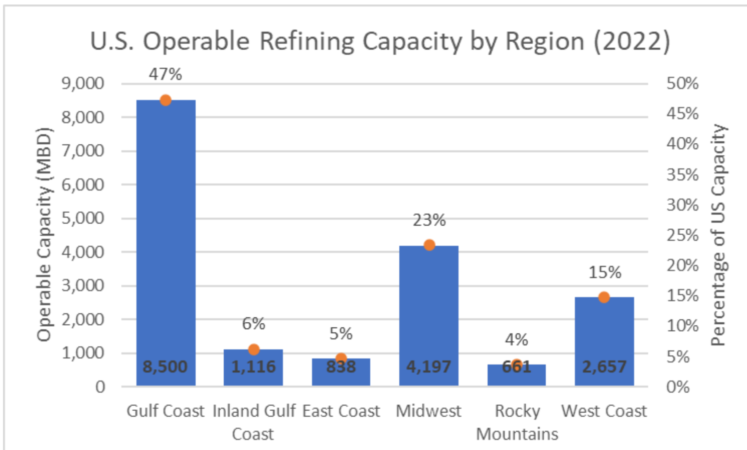

Figure 1. US Operable Refining Capacity by Region (2022). Source: EIA[2]

Problem Statement & Objective

This project aims to test and describe the effects hurricanes and tropical storms can have on the price of transportation fuels along the Gulf Coast.

Business Justification

Understanding the effects of tropical disturbances on fuel prices is important to fuel suppliers and government entities as they attempt to lessen cost impacts to consumers during major supply disruptions. Price stability information could drive decisions involving production, storage, location of refineries, environmental/governmental policy alleviations, and other strategic plans. Fuel prices also hold significant political and economic importance with impacts to the military, trade balances with other nations, and cost inflation.

The following table lists domain specific abbreviations used throughout this document [**Table 1**].

[1] The Atlantic Hurricane Season occurs annually from June 1 to November 30, with peak activity in the months of August and September. The regional area encompasses the Atlantic Ocean, Caribbean Sea, Gulf of Mexico with storm landfalls commonly experienced in Caribbean Islands, Central America, the US East Coast, and states bordering the Gulf of Mexico.

[2] Gulf Coast includes the refineries within 100 miles of the coastal borders of Texas, Louisiana, Mississippi, and Alabama.

Table 1: Abbreviations Included in Report

Abbreviation	Definition
Brent	Brent Crude Oil
C1-5	Category of Hurricane
CPG	Cents Per Gallon
DHS	Department of Homeland Security
DOE	Department of Energy
EIA	Energy Information Administration
HIFLD	Homeland Infrastructure Foundation-Level Data
HURDAT2	National Hurricane Center's HURricane DATa 2nd generation database
Jet	Jet fuel
PADD3	Petroleum Administration for Defense District 3
RUL	Regular Unleaded Gasoline
SPR	Strategic Petroleum Reserve
TD	Tropical Depression
TS	Tropical Storm
ULSD	Ultra Low Sulfur Diesel
USGC	United Stated Gulf Coast
WTI	West Texas Intermediate crude oil

Supporting Literature Survey Findings

Given the importance of the fuels value chain to US consumers and industries, the impact of hurricanes on commodity pricing is widely studied following major storms. This topic is the source of testimony by industry stakeholders and trade organizations to the US Senate and House Committees. Much of the research we reviewed was targeted on the retail station pricing impacts to assess if price gouging of consumers occurred.

In the article "*Temporary Wholesale Gasoline Price Spikes Have Long-Lasting Retail Effects: The Aftermath of Hurricane Rita*," Matthew S. Lewis primarily discusses the effects on retail prices as gasoline prices temporarily spike in the aftermath of Hurricane Rita in 2005. His study proves there are long-lasting geographical differences in retail prices following the hurricane, which supports our hypothesis and the significance of studying the impacts of hurricanes on gasoline prices. Meanwhile, the article "*Hurricanes and Gasoline Prices Gouging*" explores the effect of hurricanes on various gasoline prices such as retail and wholesale using data input from more than 4.7 million daily station-level retail gasoline prices. Based on this study, the authors concluded that while there is no widespread price gouging before, during, or after hurricanes, there are short-term effects as predicted by supply and demand theory. Similarly, Gbadebo Oladosu dives into exploring how gasoline price changes are impacted by hurricane events and anti-gouging laws in his article "*Bubbles in US Gasoline Prices: Assessing the Role of Hurricanes and Anti-Price Gouging Laws.*" Analysis indicates that from 2000 to 2017, changes in price lasted up to 4 weeks or longer. While hurricane events cause an increase in rate of price explosivity following a shock, anti-price gouging laws help counteract these effects.

The final supporting article "*The Behavior of Crude Oil Spot and Futures Prices around OPEC and SPR Announcements: An Event Study Perspective"* examines the change in crude oil prices following the events named in the title, which is similar to the method we use to study the effects following hurricane events. From 1983 to 2008, the authors found that OPEC production cut and Strategic Petroleum Reserve

(SPR) announcements were each followed by statistically significant short-term changes in crude oil prices. Our hypothesis postulates similar event-based changes to prices following hurricanes.

Through these articles, it is evident that there is plenty of ongoing study on the impact of hurricanes and other discrete events on retail prices of fuels. However, there is not much research on the impact on spot prices of gasoline, or on the price impacts to other transportation fuels such as ULSD and jet fuel. This is where our research helps provide additional insight.

Data

Data Sources

Multiple datasets were compiled to create a master data table for analysis within this project. The data sources utilized include the following:

- USGC Spot Gasoline, Jet Fuel and Diesel Prices, Daily:[3] This data is published by the Department of Energy's (DOE) Energy Information Administration (EIA). It contains the daily (Monday – Friday) spot price for:
    a. USGC conventional regular gasoline (RUL) from June 2, 1986 to present;
    b. USGC ultra-low-sulfur No. 2 Diesel Fuel (ULSD) from June 14, 2006 to present;[4]
    c. USGC kerosene-type jet fuel (Jet) from April 2, 1990 to present.

  Pricing data is utilized as a dependent variable in the analysis as the change in prices pre- and post- storms are analyzed.
- West Texas Intermediate (WTI) Crude Oil Prices, Daily:[5] This data is published by the DOE's EIA. It contains the daily (Monday – Friday) spot price for WTI Crude Oil from January 2, 1986 to present. WTI is a blended crude oil stream from West Texas and Southern New Mexico. It is priced and widely traded at a major crude oil storage and pipeline interchange location in Cushing, Oklahoma, and has become the benchmark crude oil for NYMEX trading. This dataset is utilized in the analysis of price changes pre- and post- storms to isolate the price change impacts from the finished transportation fuels from the upstream feedstock input prices (i.e. gasoline minus crude oil prices).
- Tropical Disturbance Data:[6] The data source for this step is the National Hurricane Center's HURricane DATa 2nd generation (HURDAT2) database, which contains Atlantic Tropical Disturbance data in 6-hour increments from 1851 to present. Key information from this database includes storm names, storm formation and end dates, landfall dates, windspeeds, and storm locations.
- Supplemental Research to Create a Unique Dataset: Each of the storms from 1998 to present that made landfall were researched to identify the location of landfall. These locations were flagged with a new feature variable based on geographic region, which corresponds to refining regions (such as Corpus Christi, TX, Houston, TX, New Orleans, LA, etc.) versus other non-refining geographic regions (such as Florida and South Texas). Additional supplemental datasets that were added included:
    a. DHS' HIFLD dataset,[7] containing latitude and longitude coordinates of all petroleum refineries in the United States.

[3] Spot Prices for Crude Oil and Petroleum Products, https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.htm.
[4] Diesel sulfur specifications in the United States changed to an ultra-low sulfur requirement in 2006. The EIA only provides spot price data in the USGC from this date onward.
[5] Europe Brent Spot Price FOB (Dollars per Barrel), https://www.eia.gov/dnav/pet/hist/RBRTED.htm.
[6] https://www.nhc.noaa.gov/data/hurdat/hurdat2-format-atl-1851-2021.pdf
[7] https://hifld-geoplatform.opendata.arcgis.com/datasets/oil-refineries/explore

b. EIA's PADD 3 (USGC)[8] Refinery Crude Oil Inputs, Gross Inputs, Operable Capacity, and Utilization. This dataset, although mentioned in the proposal, was only useful for supplemental analysis outlined in the appendix.

Data Cleaning and Transformations

The team started the data cleaning process by pulling storm data from the HURDAT2 dataset from 1998 to 2022. This dataset includes the storm name (possibly "Unnamed"), year, start date prior to landfall, end date after landfall, landfall date, max wind speed, storm class (tropical storm or hurricane categories 1 through 5), and a storm tracker identification number. With additional storm trajectory research, a binary variable "Landfall US" was added. 1 represents landfall in the US and 0 represents no landfall or landfall outside of the US. Location of landfall was categorized utilizing a regional naming convention through storm research. Another binary variable, "Refining Center," was added manually indicating which storms had made landfall near refining centers. Using additional research, storms that made landfall were labeled with a 1 and all others were categorized as a 0.

After the storm geographic information was aggregated, 29 days of transportation fuel and WTI spot prices were added to the dataset from the USGC Spot Prices daily datasets from the EIA. These datasets include prices from the 14 days prior to landfall, the price on the landfall date, and prices for the 14 days following landfall. Additionally, the commodity "crack" (i.e., gasoline price minus WTI crude oil price) was calculated for each day. Notably, commodity prices are not tracked and recorded on weekends, however, hurricanes can fall on any day of the week. We utilized two versions of our dataset to account for this hurdle: one in which the previous day price (typically Friday) was utilized for missing data (which is common practice in the oil industry but may cause the pre-storm and post-storm analysis to show lower price changes than expected) and one in which days with missing data were eliminated from the analysis. The implications of this change are discussed later in the paper.

This data cleaning process allowed the team to analyze the change of transportation fuel spot prices and cracks per location and category of storm.

Exploratory Data Analysis

As part of data exploration phase, the team combined the HURDAT2 and the HIFLD datasets to investigate the storms geographically. By using the two datasets it was possible to visualize the locations of all storm trajectories in our analysis period, 1998 to 2022, with respect to the location of refineries located in the PADD3 region[9] [**Figure 2** & **Figure 3**].

[8] https://www.eia.gov/dnav/pet/pet_pnp_wiup_dcu_r30_w.htm

[9] Petroleum Administration for Defense District (PADD) 3 is a geographical grouping of states located along the USGC. The US has 5 PADDs which were created during World War II for rationing of gasoline. While gasoline is no longer rationed, these 5 districts are still utilized for tracking and analyzing commodity production, consumption and movement data by the DOE. U.S. Energy Information Administration - EIA - Independent Statistics and Analysis

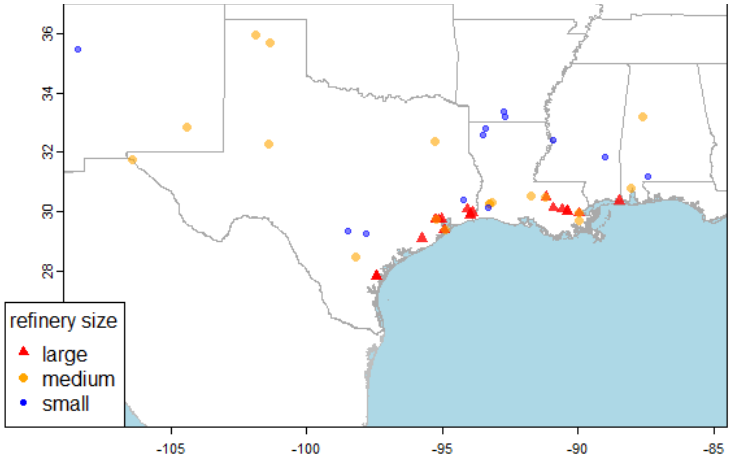

Figure 2. Location of All US PADD3 Oil Refineries and Their General Capacity as Given by HIFLD.

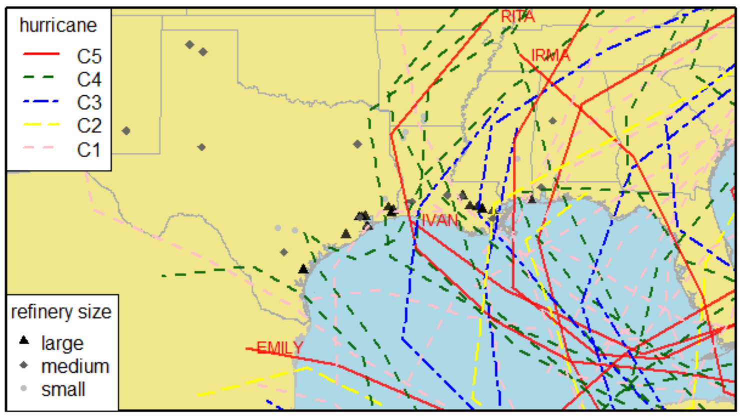

Figure 3. Trajectory of All Hurricanes (Excluding Tropical Storms) in the Gulf Coast, 1998-2022.

From the generated visuals, as well as storm counts, it was evident that the total count of tropical storms vastly outnumbered the count of hurricanes. The proportion of historical storms that were hurricanes is significantly smaller than what the authors originally expected. Furthermore, it was also apparent that the total amount of storms that hit refineries in PADD3 would be an even smaller subset. Given this knowledge, the team tried different approaches to avoid limiting the dataset. The appendix outlines some of this additional analysis.

In review of the selected price sets, WTI crude oil, Brent crude oil, and transportation fuels seem to move as a cohort, which is logical since the flat crude oil price level should drive the prices of derivative products, such as gasoline, ULSD, and jet fuel [**Figure 4**]. It is worth noting that some movements in crude oil pricing could be due to macroeconomic and/or geopolitical events, such as the 2008 global recession or the 2022 Russia/Ukraine war and resulting sanctions. Speculative factors that have the potential to impact the author's analysis are listed in the conclusion.

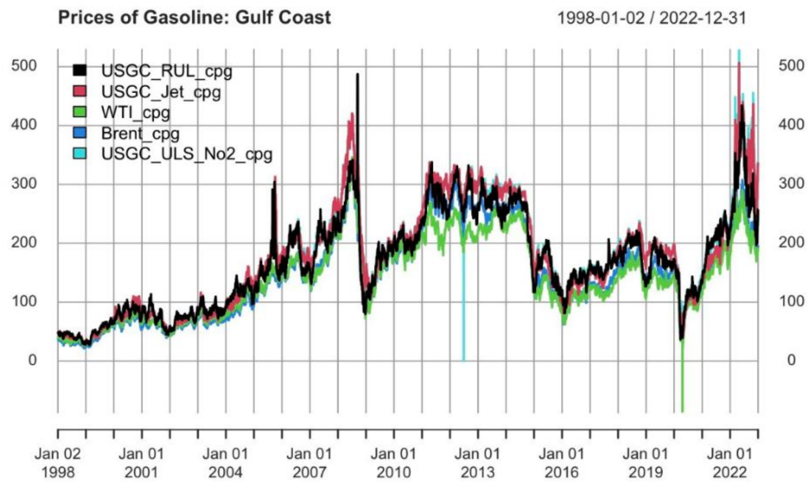

Figure 4. Historical Price Data of Transportation Fuels.

Using the cleaned dataset, we plotted cumulative spot gasoline price changes[10] from 14 days prior to landfall to 14 days after landfall by category of storm and landfall location [**Figure 5**]. From these preliminary charts, there appears to be no meaningful change in price for storms that did not make landfall or impacted land in an area without refineries.

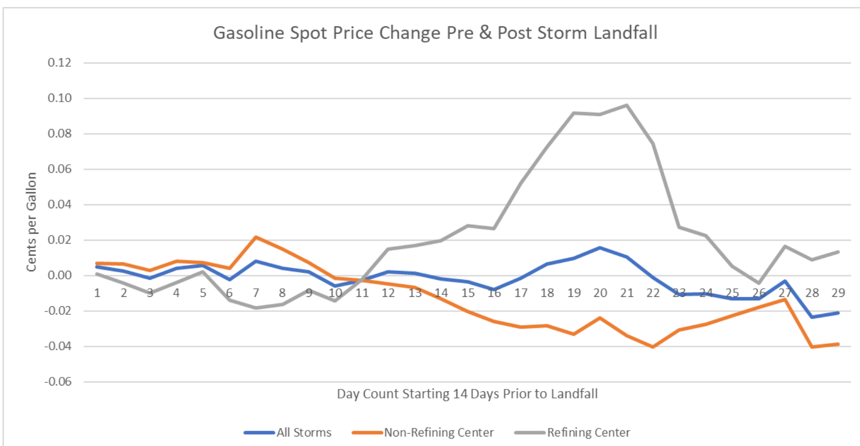

Figure 5. Gasoline Spot Price Change Pre & Post Storm Landfall, Refining Center vs Non-Refining Center. Note: Landfall occurs on day 15.

Further, there does not appear to be an impact on spot gasoline prices from tropical disturbances, tropical storms, or hurricane categories 1 through 3 that made landfall in the vicinity of refining locations, which includes 426 storms. Alternatively, category 4 storms making landfall near refineries correlate to a significant spike in spot gasoline prices from the landfall dates to over a week after landfall. The impact for similar category 5 storms follows the same pattern to greater effect [**Figure 6**].

[10] Day 1 on the chart is price 14 days prior to landfall. All subsequent daily prices are compared to this starting point to understand the cumulative price movement compared to this date.

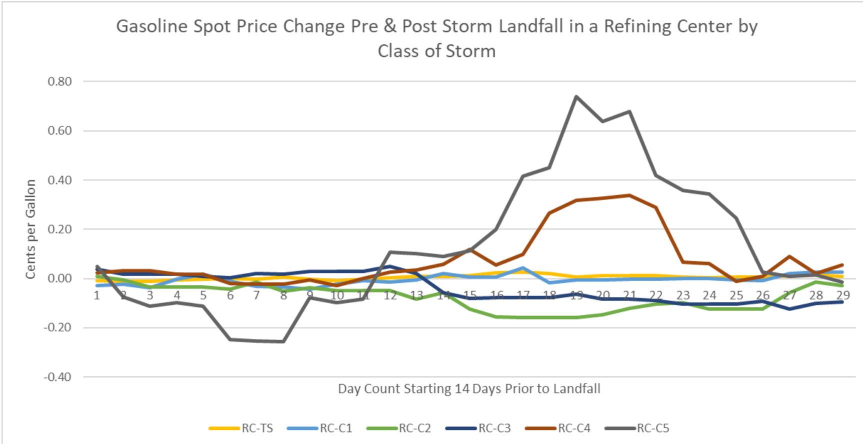

Figure 6. Gasoline Spot Price Change Pre & Post Storm Landfall, Refining Center by Class of Storm. Note: Landfall occurs on day 15.

There is a significant caveat to these results as only seven category 4 hurricanes and two category 5 hurricanes meet the filtering criteria from 1998 to 2022. The team bolstered the filtered dataset by including additional refinery output fuels, including Jet and ULSD (Diesel). While we recognize that the dataset of major storms is limited, it still provides an informative piece of analysis for an event study.

Key Variables

Independent variables include categorical variables for pre-storm period, landfall period, post-storm period, and strength of storm.

- Pre-storm period refers to the period from 14 days prior to landfall to 3 days prior to landfall.
- Landfall period refers to the time window from 3 days prior to landfall to 3 days post landfall.
- Post-Storm period refers to the time window from 3 days post landfall to 14 days post landfall.
- Strength of storm refers to the storm categories of tropical depression (TD), tropical storm (TS), category 1 (C1), category 2 (C2), category 3 (C3), category 4 (C4), and category 5 (C5). These storm categories are defined by the National Hurricane Center and related to the wind speeds achieved during the active storm window. This strength of storm category was eventually narrowed to incorporate Major Storms (category 4 and 5) as a factor variable.

Approach/Methodology

Approach

Following review of the literature referenced previously, we selected an event study approach to the analysis. The goal with an event study approach is to test whether there is a statistically significant difference in the dependent variable in a period of time before and after an event, which in this case was evaluating tropical disturbance effects on spot commodity prices.

Feature Selection

To better understand the data, box plots of different daily price changes were created against storm classes that resulted in a landfall in a refining center. Note the historical transport fuel price datasets only included information for the standard US work week, Monday to Friday. To account for storms that had an impact over a weekend, Friday's price was extrapolated to the weekends. Based on the data in **Figure 7** and **Figure 8**, it can be observed that the price of USGC_RUL and USGC_Jet tends to vary significantly for storm classes C4 and C5, which applies to both daily price change and crack[11] change.

[11] See description of crack earlier in the paper.

For USGC_No2,[12] price varies most for storm class C4, however, the price dataset for this category is most limited since it did not start until 2006. This indicates that the class of the storm plays a critical factor in the price change.

When defining the regression models described in the next session, it was also noted that the p-values for storms with categories 4 and 5 were significant, while those for lesser-strength storms were not. Therefore, to avoid overspecification of the model, a single factor variable for "Major Storm" was selected rather than individual storm class.

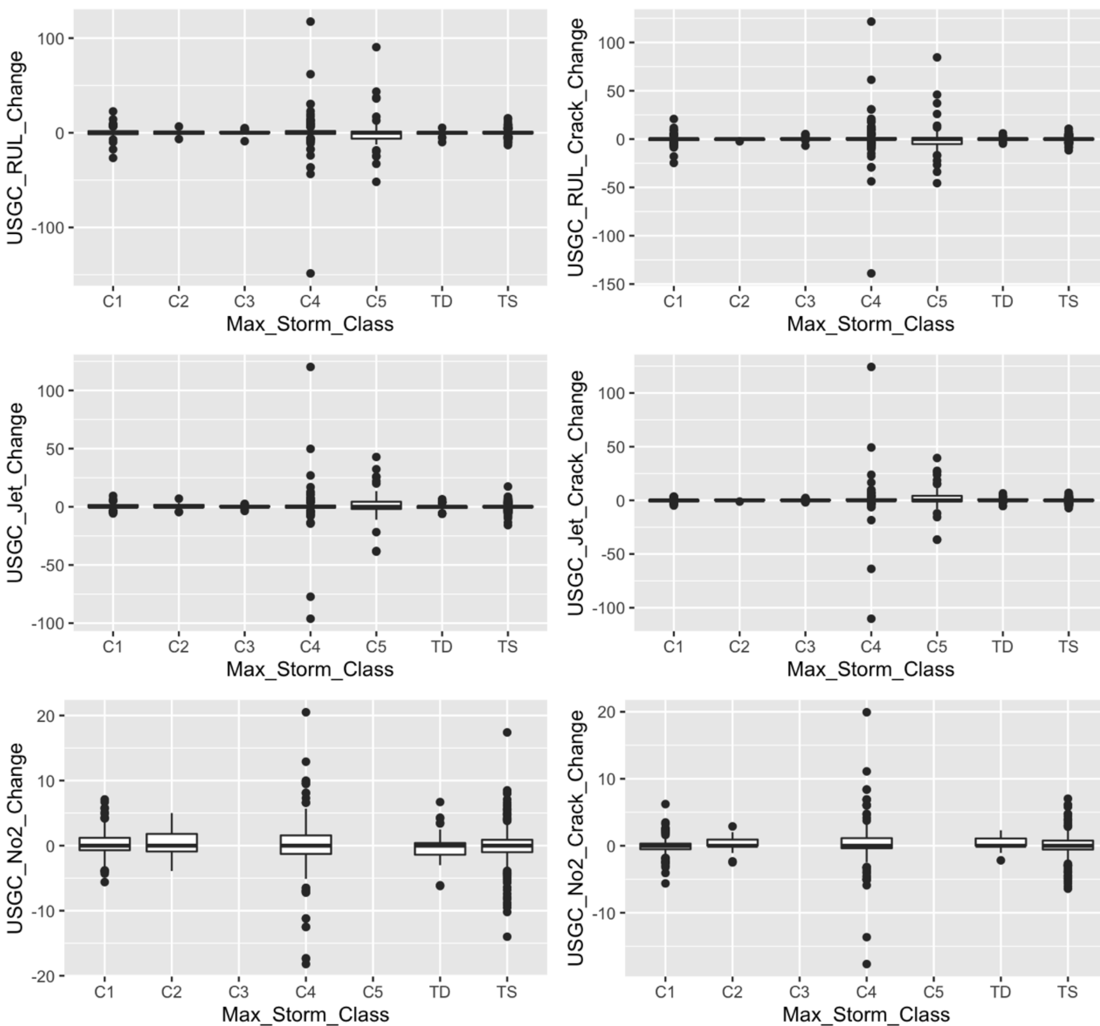

Figure 7. Boxplot of Price Change Against Storm Class with Weekend Price Estimates

[12] No2 refers to No. 2 Distillate Fuel oil which is another name for ULSD.

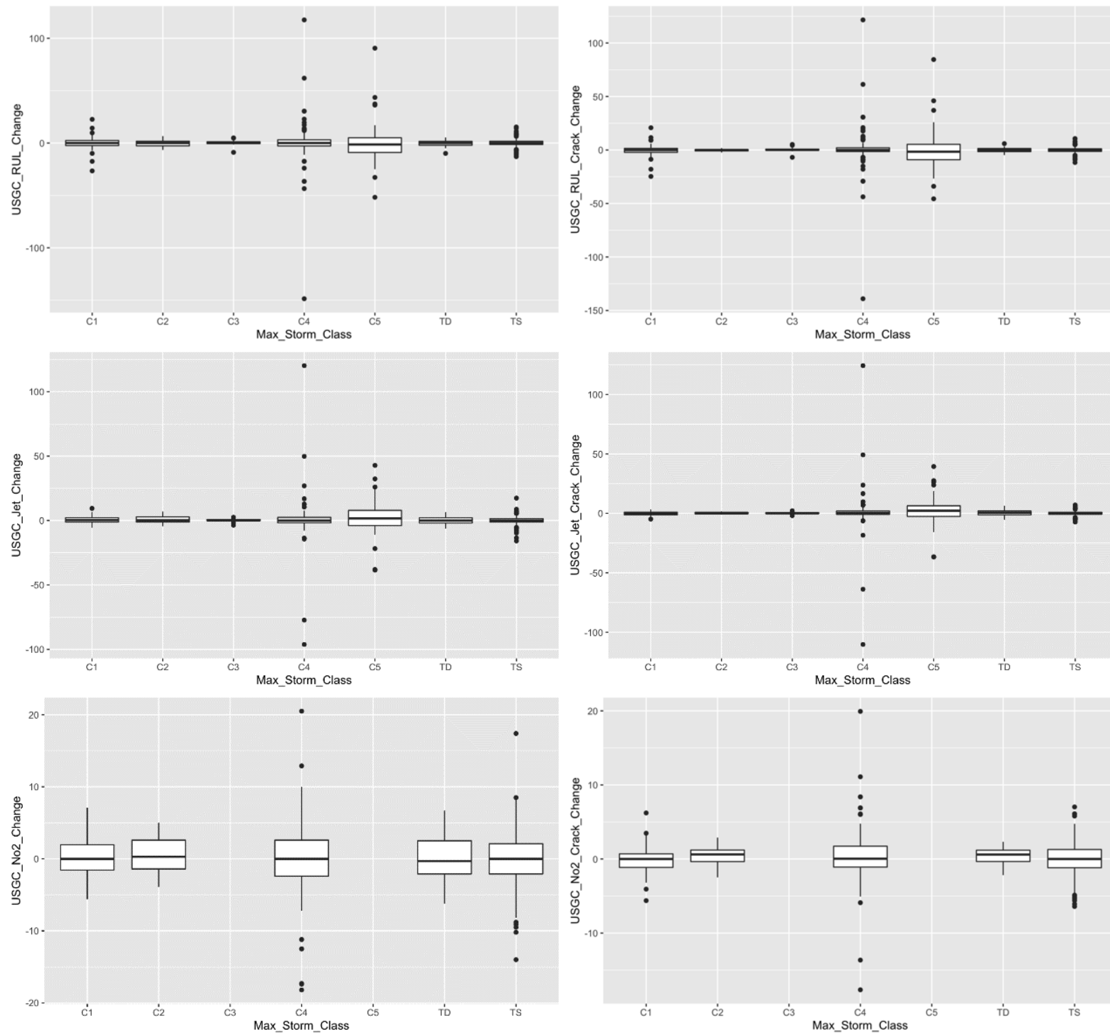

Figure 8. Price Change Against Storm Class without Weekend Price Estimates

The next feature variable selected was a factor variable for the time periods of pre-storm, landfall, and post-storm windows. In our exploratory data analysis, it was noted that most storms are short in duration, therefore the event windows for pre-storm and post-storm do not need to cover a wide range of dates. Additionally, the research from Beatty[13] and Demirer[14] utilized 14-day windows around major events to capture the event window and lower the risk of other events clouding the results.

Other feature variables such as year, refining capacity at risk, and specific refining center at risk were tested, but ultimately excluded due to the risk of overfitting the model. For example, year was tested to see if we could quantify the level of price change over time to see if storms have become more or less impactful to spot prices. However, with so few storms per year, this feature risks overspecification. Additionally, individual refining centers along the gulf coast such as Corpus Christi, Houston, and New Orleans were tested but had a similar result of potential overspecification. Refining capacity at risk was similar to refining center and was therefore excluded as potential variable as well.

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[13] Beatty, T. K., Lade, G. E., & Shimshack, J. P. (2021). Hurricanes and Gasoline Price Gouging. Journal of the Association of Environmental and Resource Economists, 8(2), 347–374
[14] Demirer, R., & Kutan, A. M. (2010). The behavior of crude oil spot and futures prices around OPEC and SPR announcements: An event study perspective. Energy Economics, 32(6), 1467–1476.

Modeling

Based on the exploratory analysis and feature selection, the response variable was determined to be the cumulative change in price, while the independent variables include categorical variables for 14 days prior to the landfall, landfall period of 7 days, 14 days post landfall, and storm category. With the landfall period and storm categories excluding C4 and C5 taken as the baseline factors for the model, the linear regression model is represented as below:

$$PriceChgCu = \alpha + \beta * PreStormPeriod + \gamma * PostStormPeriod + \lambda * MajorStorm$$

Where:

$PriceChgCu = Response\ variable\ of\ cumulative\ price\ or\ crack\ change$

$\alpha = Intercept$

$\beta = Coefficient\ for\ pre - storm\ period\ of\ 14\ days\ prior\ to\ 3\ days\ prior\ to\ the\ landfall$

$\gamma = Coefficient\ for\ post - storm\ period\ of\ 3\ days\ to\ 14\ days\ post\ landfall$

$\lambda = Coefficient\ for\ Major\ Storm\ category\ of\ class\ C4\ or\ C5$

Models were built for gasoline flat price and crack, ULSD flat price and crack, Jet fuel flat price and crack, and WTI crude oil flat price. Since there is no price or crack recorded for the weekends, two approaches were taken: the first approach was to set the price to be the same as Friday's price while the second approach was to exclude dates that fell on Saturday and Sunday altogether. Thus, seven models were built using the first approach, and seven more models were built using the second approach.

Results

Our analysis resulted in a model based on the cumulative price and crack change against the pre-storm window (the 14 days prior to the storm), post storm window (the 14-days following the storm), and factor for major storm [**Table 2**].

Table 2: Model Results

Cumulative Price	Description	ULSD_Crack	
		With Weekend	**Without Weekend**
USGC_RUL_Change	Gasoline – Flat Price	0.0788	0.0896
USGC_RUL_Crack_Change	Gasoline - Crack	0.1008	0.1131
USGC_ULSD_Change	ULSD – Flat Price	0.0019	0.0019
USGC_ULSD_Crack_Change	ULSD - Crack	0.1591	0.1711
USGC_Jet_Change	Jet Fuel – Flat Price	0.0990	0.1047
USGC_Jet_Crack_Change	Jet Fuel - Crack	0.1518	0.1635
WTI_Change	WTI – Crude Oil Flat Price	0.0290	0.0258

The results in **Table 2** show the adjusted R-squared values for all the models are relatively low, indicating that the model does not explain much of the variability in the cumulative price change. Models that do not consider prices on the weekend have a slightly higher R-squared value. Moreover, it can also be observed that amongst these models, ULSD-Crack has the highest R-squared value when modeled with cumulative price change and without the weekends.

Narrowing in the crack versions of the without weekend versions of the models, our feature variables are significant at the 10% level for the Post-Storm and Major Storm variables in all versions of the models

[**Table 3**]. The intercept in this model would represent the landfall period due to the third factor definition for the time window.

Table 3: Model Coefficients

	RUL_Crack		**ULSD_Crack**		**Jet_Crack**	
Variable	Coefficient	P-Value	Coefficient	P-Value	Coefficient	P-Value
Intercept	-1.196	0.3662	-2.223	0.0019*	-1.999	0.0789*
Pre-Storm	-2.944	0.0726*	0.1947	0.8235	-1.153	0.4128
Post-Storm	3.165	0.0523*	1.7052	0.0507*	5.023	0.0004*
Major Storm	13.453	<2e-16*	7.4312	<2e-16*	14.242	<2e-16*

The statistically significant results from the model indicate that we find post-storm price increases in the range of 1.71 to 5.02 cents per gallon. If a major storm is indicated, this can increase the price level by an additional 7.43 to 14.24 cents per gallon.

Alternate Approaches

Additional analysis was conducted on the dataset that did not yield significant results. Details regarding that analysis can be found in the Appendix.

Conclusion

In summary, estimating the direct impact on transportation fuel prices by storms is hard, at best. We estimate that impacts to transportation fuel prices are primarily experienced with Category 4 and 5 storms with some significance, but impacts from lesser storms that hit refining centers cannot be quantified with certainty. There are many factors that are likely to cause large price swings in the cost of transportation fuels such as geopolitical events, global supply and demand, economic recessions, and general market sentiment. Although storms are but one of many factors, it is useful to know the size of storm that might impact refinery capacity. A recent study has concluded that there is an upward trend of increasingly powerful hurricanes (Kossin et al., 2020). Having a historical perspective regarding the types of storms that have made landfall in the USGC can help inform stakeholders on how best to prepare for future storms.

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Appendix

While exploring the datasets, we made different attempts to explore possible relationships between storms and their impact on refineries. In addition to predicting a storm's impact on price directly, the team also attempted to use other refinery variables as the response, which is summarized in this appendix.

Predicting PADD3 Refineries Capacity Utilization

The first attempt to use a different response variable was to substitute "Percent Utilization," a data point in the EIA's PADD3 dataset regarding refinery operational capacity. According to the EIA[15], "Percent Utilization" is a source of information which is defined as "…the utilization of all crude oil distillation units. The rate is calculated by dividing gross inputs to these units by the operating/operable refining capacity of the unit." The team speculated that a strong storm might cause a significant drop in the percentage utilization of refineries in the PADD3 region.

Utilizing the data in HIFLD, the team first filtered out refineries not included in PADD3, including refineries in Mexico and refineries *not* in the US states of Alabama, Arkansas, Louisiana, Mississippi, New Mexico, or Texas. Using the storm historical location in HURDAT2, a set of continuous variables was made to indicate the distance of each storm with respect to each refinery on a day-by-day basis. After completing the distance calculations (using the R package geosphere), there were 59 additional variables, each indicating the distance to a particular refinery. These additional features, along with the maximum windspeed of each storm, were then input as independent variables to a linear regression model with the previously mentioned "Percent Utilization" as the response.

The resulting model, although interesting, indicated a weak fit with an adjusted R-squared value of less than 0.01. The maximum windspeed was significant at a p-value less than 0.05, signaling there was a strong negative relationship between a storm's strength and the total utilization of the refineries in the PADD3 region. The poor performance of the model might be attributed to the independent factors being strongly correlated. A possible area of future research is to reduce the number of refineries included in the regression, especially by removing the smaller refineries.

Predicting PADD3 Refineries Net Input

A second attempt was made to use another response variable, "Net Input," that is also included in the EIA's PADD3 dataset. "Net Input" is a measure of the amount of crude oil (amongst other materials) that is required by refineries to generate other fuel products as an output of the refining process. The team speculated that a strong storm might directly impact the amount of crude oil that is imported by refineries and by extension possibly cause a price increase. The same independent variables were used (the distance to all PADD3 refineries and the storm's maximum windspeed) in the regression. The resulting model performed significantly better with an adjusted R-squared value of 0.1021. Although the low adjusted R-squared value does not indicate a strong fit, it is comparable to some of the other results outlined in the report. Consistent with the first model in this appendix, the maximum windspeed was significant at a p-value less than 0.05. However, maximum windspeed is redundant (strong correlation) with the storm category factor variable used in the final model of this paper. Including this factor in our model would have introduced multi-collinearity so we opted not to include it.

[15] https://www.eia.gov/dnav/pet/TblDefs/pet_pnp_wiup_tbldef2.asp