THE ECONOMIC IMPACT OF HURRICANES AND HURRICANE FORECAST ACCURACY ON THE U.S. GULF COAST OIL AND GAS INDUSTRY

A Dissertation

by

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Submitted to the Graduate and Professional School of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

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May 2022

Major Subject: Agricultural Economics

ABSTRACT

The Gulf Coast is the most important U.S. oil and gas region and contains substantial industry infrastructure and assets. The coastal location makes that energy infrastructure vulnerable to extreme weather like hurricanes, and projections show that climate change may worsen the situation. This dissertation examines the impact of hurricane forecasts on aspects of the Gulf Coast oil and gas industry. The analysis is based on two data sources. First, we used refinery oil input and offshore production data to portray industry activity. Second, we used NOAA information on hurricane forecasts and resultant incidence. Then in three essays, we studied hurricane and associated forecast effects on oil input and offshore operations as well as the effects of inaccurate forecasting.

In the first essay, we explore the relationship between the oil input to refineries and forecast hurricane characteristics using econometrics. In the second essay, we study relationships between forecast hurricane characteristics and offshore platform production shutdowns and evacuations. In the third essay, we study the effects of hurricane forecast inaccuracies in terms of refinery oil input.

Across these essays, we find that stronger hurricane forecasts are associated with offshore shutdowns and oil input reductions and in turn substantial economic losses. In addition, we find hurricane forecast inaccuracy adds to economic losses.

DEDICATION

To my dear family

ACKNOWLEDGEMENTS

I would like to express my deepest gratefulness to my committee chair, Dr. Bruce A. McCarl. During my journey to pursue Ph.D. in the field of Agricultural Economics at Texas A&M University, Dr. McCarl not only taught me knowledge using his years of experience and expertise but also gave me big support and confidence every time I came across academic and emotional challenges. He always thinks best for his students, finds and provides good opportunities that could benefit us in academic career and/or experience. I feel really grateful to be one of his students.

I would also like to express my great thanks to my committee members, Dr. Ximing Wu, Dr. Richard T. Woodward, and Dr. Yangyang Xu. I was in Dr. Wu's and Dr. Woodward's classes, and I learned a lot from them and still remember Dr. Wu's detailed blackboard notes and Dr. Woodward's passion in class. I also remember Dr. Xu's big support and encouragement as well as good patience in answering my questions. I really thank them for their willingness to be my committee members and provide great comments and deep insights on my research.

Thanks also go to my friends and colleagues and the department faculty and staff for making my time at Texas A&M University a great experience. I would like to thank Chengcheng for giving me so much academic support as a senior student at that time during my study. I thank Yabin for being my colleague and studying together to pass the resource prelim exam. Also I would like to thank Chenrui for being kind and patient to

answer my questions about weather data, which was helpful especially at the beginning of the research when I was totally new to the field.

Last but not least, I would like to thank my father and mother. Their love is the biggest spiritual support for me. Also, I am thankful for my boyfriend Binbin for his accompany, understanding, patience, and love.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supervised by a dissertation committee consisting of Professors Bruce A. McCarl, Ximing Wu, and Richard T. Woodward from the Department of Agricultural Economics and Professor Yangyang Xu from the Department of Atmospheric Sciences.

Specifically, I had substantial interaction with Dr. Bruce A. McCarl and Dr. Yangyang Xu while doing Chapters 2 and 3. Dr. Ximing Wu, Dr. Richard T. Woodward, and Dr. Chengcheng Fei also provided good insights. Chapter 4 was done with substantial interaction with Dr. Bruce A. McCarl, and Dr. Xu also gave good suggestions.

All work for the dissertation was completed by the student but benefitted from advice from others.

Funding Sources

Graduate study was supported by a fellowship from Texas A&M University and a dissertation research fellowship from Texas A&M Energy Institute. I also appreciate the funding support for my appointment as a Graduate Teaching Assistant in the Department of Agricultural Economics. The contents of this dissertation are solely my responsibility and do not necessarily represent the official views of the organizations mentioned above.

NOMENCLATURE

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BSEE	U.S. Bureau of Safety and Environmental Enforcement
EIA	U.S. Energy Information Administration
NHC	U.S. National Hurricane Center
NOAA	U.S. National Oceanic and Atmospheric Administration
NWS	U.S. National Weather Service
PADD 3	Petroleum Administration for Defense District 3 which covers the Gulf Coast as defined by the US government and administered by the United States Department of the Interior's Oil and Gas Division.
SSHWS	Saffir–Simpson Hurricane Wind Scale

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1. INTRODUCTION

The U.S. Gulf Coast is the most prominent oil and gas production/refining region in the U.S., as it contains more than 47% of the nation's petroleum refining capacity as well as over 50% of the nation's natural gas processing capacity. Also, it contains about 15% the nation's offshore oil production and 5% of its offshore natural gas production (EIA, 2019a). Furthermore, according to a 2013 Texas Sea Grant publication, which drew information from a study by Entergy, energy assets on the Gulf Coast, predominately located in Texas and Louisiana in Gulf Coast, are worth approximately $800 billion (Texas Sea Grant, 2013).

However, the Gulf Coast oil and gas assets are vulnerable to extreme weather events. The region has experienced flooding events at an unprecedented frequency in recent years (with multiple floods in the 100 to 500-year classes within just the last decade). It is also impacted by hurricanes landing in this region with 24 storms in about last two decades. We've also observed increased Gulf of Mexico sea surface temperatures and rising sea levels which are key factors in intensifying the strength of hurricanes and their ability to penetrate inland. Furthermore, climate change is contributing to both warmer waters and increased sea levels. Such developments make it likely we will face a future with more severe and more damaging hurricanes. Also damages to infrastructure including energy systems have been large under recent major hurricanes (e.g., major damages occurred under hurricane Harvey in 2017). Climate change related projections show the threat is likely to increase in future.

In this study I examine the economic damages associated with previous hurricanes. In particular, I will study the impact of hurricanes on oil inputs to refineries and the operation of offshore platforms on the U.S. Gulf Coast.

This is not the first study to address economic impacts of hurricanes. Some studies have examined impacts on the general economy level (Nordhaus, 2006; Petterson et al., 2006; Strobl, 2011; Strobl, 2012; Coffman and Noy, 2012), while others have focused on a specific sector like agriculture (Chen and McCarl, 2009), general business (Burrus Jr et al., 2002; Gordon et al., 2010; Zhang et al., 2009), tourism (Coffman and Noy, 2012), and energy (Fink et al., 2010; Reed et al., 2010). However, most of them address direct physical damages and losses caused by past hurricanes. In fact, the impact of hurricane is not only embodied in direct effects like damages due to flooding associated with heavy rainfall or damages due to high wind speeds. There are also losses due to suspended business operations such as an anticipatory shutdown of oil and gas production and processing which reduces revenue and profits. We cannot find studies addressing this latter issue, so our study will focus mainly on changes in operational levels and not on direct physical damages. Furthermore, we believe in terms of anticipatory actions that refineries and offshore platforms make shutdown and processing reduction decisions based on hurricane forecasts. But such forecasts could be inaccurate and thus cause anticipatory actions to occur when they're not needed and can cause regions to not take anticipatory actions when they would have been appropriate. The business interruption costs borne under such circumstances could be reduced by more accurate forecasts and we will try to estimate costs and effects under such circumstances.

This thesis contains three essays that are developed to contribute to the research directions mentioned above:

The first essay (Chapter 2) examines the impact of NOAA-issued hurricane strength and projected impact path characteristics on oil inputs to petroleum refineries located on the Gulf Coast and estimates the economic loss resulting from the reductions in those inputs.

The second essay (Chapter 3) examines the economic impact of hurricane wind speed forecasts, but this time looks at consequences for shutdowns of offshore oil and gas production platforms.

The third essay (Chapter 4) extends the first essay examining forecast accuracy considering possible errors in terms of wind speed and region impacted as it influences refinery oil input estimating the economic loss from forecast inaccuracy.

2. THE ECONOMIC IMPACTS OF HURRICANE ON THE U.S. GULF COAST PETROLEUM REFINERIES

2.1. Introduction

The Gulf Coast area is an important region in the U.S. oil and gas system. A huge amount of oil and gas industry resources and infrastructure are present in this region, both onshore and offshore. According to the Energy Information Administration (EIA, 2019a), 17% of the total U.S. crude oil production and 5% of U.S. natural gas production arise from offshore wells in the Gulf of Mexico. Additionally, 45% of total U.S. petroleum refining capacity and 51% of total U.S. natural gas processing capacity are located onshore in the Gulf Coast.

This region is vulnerable to extreme weather events like hurricanes and consequently the energy industry is vulnerable. For example, in 2017, hurricane Harvey that made landfall in Texas, caused the shutdown of approximately 2.2 million barrels per day of processing capacity or roughly 45% of the Texas Gulf Coast capacity (Jacobs, 2017). While this is of current concern it is also true that there are projections indicating that under climate change the intensity and frequency of hurricanes is likely to increase (Nordhaus, 2006).

Vulnerability arises as elements of petroleum refining can be greatly affected by hurricane winds and precipitation. Equipment such as empty tanks, roof tops, piping, and connections between storage and processing units are vulnerable to high winds (Cruz and Krausmann, 2013; Schaeffer et al., 2012) while flooding as another concern

(Knudson et al., 2020). In 2007, refineries in Corpus Christi and Houston area were closed due to Hurricane Harvey (CNN Business, 2017).

Recent hurricanes have damaged the industry and it is likely that under continuing climate change those damages may increase (US EPA, n.d.). Thus, this research will examine the impact of the hurricane on petroleum refining activity in the U.S. Gulf Coast energy sector.

2.2. Background

This study focuses on hurricane influences on the energy sector and the resultant economic impacts. There are several bodies of the literature that deal with components of that issue, and we will cover general economic damage estimates associated with hurricanes, energy sector influences from hurricanes and methods employed for hurricane related analysis.

2.2.1. General Hurricane and Disaster Economic Damage Estimates

Many studies have addressed the economic impact of hurricanes – some studying the issue on an economy wide level, while others address influences on specific sectors or industries. Examples of general hurricane economic impact studies include (but are not limited to) studies of hurricanes' effect on GDP (Nordhaus, 2006), economic growth rates (Strobl, 2011, 2012), multiple economic sectors (Petterson et al., 2006), and regional economic and social characteristics (dominant industries, employment, population, income level, etc. - Coffman and Noy, 2012). Examples of studies addressing hurricane impacts on a specific sector or industry include (but are not limited to) those addressing the agricultural sector (Chen and McCarl, 2009), the business sector

(Burrus Jr et al., 2002; Gordon et al., 2010; Zhang et al., 2009), the energy sector (Fink et al., 2010; Reed et al., 2010), and tourism (Coffman and Noy, 2012).

2.2.2. Effects on Oil and Gas

There are also studies examining energy industry impacts. These have addressed hurricane effects on oil and gasoline prices (Fink et al., 2010), developing country economies (Strobl, 2012), and reconstruction decisions (Petterson et al., 2006; Vigdor, 2008). Most of the literature we have reviewed discusses short-term impact (Burrus Jr et al., 2002; Fink et al., 2010; Gordon et al., 2010; Nordhaus, 2006; Petterson et al., 2006; Reed et al., 2010; Tierney, 1997; Weiderman and Bacon, 2008; Zhang et al., 2009). However, Coffman and Noy (2012) investigated the long-term time to recover from hurricane impacts and indicate that the effect lasted 18 years after an event. Some of this literature concentrates on specific hurricanes (Coffman and Noy, 2012; Gordon et al., 2010; Petterson et al., 2006; Reed et al., 2010; Vigdor, 2008; Weiderman and Bacon, 2008), while others address the issue on a more general level (Burrus Jr et al., 2002; Fink et al., 2010; Nordhaus, 2006; Strobl, 2011; Tierney, 1997; Zhang et al., 2009).

2.2.3. Methods Employed

Here to broaden our literature search, we also reviewed literature that analyzed the economic impact of natural disasters (i.e., earthquakes) or other extreme weather events (Tierney, 1997; Zhang et al., 2009). That literature reveals various approaches for studying disaster impacts. Some develop direct damage estimates such as infrastructure damage or general physical damage (Tierney, 1997; Reed et al., 2010), while others investigate indirect damage like business interruption and accompanying economic loss (Gordon et al., 2010).

The methodologies used in the literature span a number of fundamental approaches. Some studies concentrate on damage accounting and / or documenting losses and aftermath issues. Others use econometric methods and explore the relationship between hurricane characteristics and economic performance.

Some literature simply focuses on event documentation and general damage discussion. Their contributions in cases derive from the large data set collected by them. Tierney (1997) documents the direct physical damages and outlines empirical findings on the ways that earthquakes affected business operations based on a large representative sample from a survey. Burrus et al. (2012) conduct a survey on industry businesses to examine the impact of low-intensity hurricanes on business interruptions finding that the cumulative impact generated by the high strike frequency of low-intensity hurricanes is equivalent to a high-intensity hurricane strike. Some studies address impacts after the hurricane departs. For instance, Petterson et al. (2006) assess the impact of hurricane Katrina on the Gulf Coast from a socio-economic perspective and discuss what happened in the policy debate on reconstruction of New Orleans and areas in the Mississippi Delta. Vigdor (2008) discusses New Orleans rebuilding from the economic perspective by comparing the equilibrium before and after Hurricane Katrina. Zhang et al. (2009) build a conceptual model that accounts for the different vulnerability dimensions (e.g., capital, labor, supplier, customer, etc.) of business effects from disasters.

There is also literature studying this issue using econometric methods. Nordhaus (2006) employed ordinary least squares (OLS) and regressed the damage-GDP ratio on maximum sustained wind speed at landfall in an effort to estimate the wind speed effect on the hurricane damage. Reed et al. (2010) used a linear regression model to estimate the relationship between utility interruption frequency and wind speed. Strobl (2011, 2012) used a fixed effect panel regression model to regress coastal county GDP growth rate as it was influenced by hurricane intensity in the form of a destruction index based on wind speeds (2011). They also extended the study to developing countries in Central America and the Caribbean (2012). Gordon et al. (2010) use a multiregional interstate economic model (NIEMO), to examine the business interruption impact of the hurricanes on the oil refining sector. Coffman and Noy (2012) use synthetic control methodology to explore the long-term impact of Hurricane Iniki that hit the Hawaiian island of Kauai in 1992 using the other unaffected Hawaiian Islands as a control group.

All of the above-mentioned studies provide valuable approaches that might be usable in hurricane (or disaster) impact estimation. Some of the literature also links hurricane intensities (e.g., wind speeds or other index calculated from wind speeds) to damages. The limitation of them, however, is that most of them use observed hurricane intensity rather than forecasted intensity. But it is likely that the shutdown decisions are made in advance of landfall based on forecasts. In this paper, we will use the forecast information on hurricane intensity and study the effects of forecasts on volume of petroleum refinery use of crude oil. Here we choose to use forecast hurricane characteristics based on a fundamental assumption that petroleum refineries and related entities make pre storm shutdown or reduced operation decisions based on forecasts and that this will be reflected in the volume of crude oil input to the refineries.

2.3. Data

We will examine the relationship between refinery crude oil usage and hurricane characteristics, trying to explore how refineries react to alternative hurricane forecast characteristics.

For estimating effects on refinery operation, we use data on weekly refiner net crude oil input as measured in thousand barrels per day to Gulf Coast refineries (those located in Petroleum Administration for Defense District 3, PADD3 (EIA, 2019d). For hurricane forecast characteristics, we use data on two main items – hurricane strength (category of the hurricane) and landfall location. Details on these data follow.

2.3.1. Weekly Refiner Net Input of Crude Oil

The main activity of refineries is to input crude oil and then refine it into petroleum products such as gasoline, diesel, and jet fuel. Both crude oil availability from production/imports and the amount of time refineries can operate are affected by hurricanes. Refineries may need to limit operations if the supply of crude oil is affected although crude oil inventory could buffer that. Also, they would limit crude oil inputs if they were shut down in anticipation of landfall. Some of these forces seem to be at work, since the data appear to show steady input on normal days but shocks during hurricane season (Figure 2.1).

The data we use is drawn from an Energy Information Agency (EIA) database (EIA, 2019d) that gives weekly refiner net input of crude oil (in thousand barrels per day). We use data for the Gulf Coast (PADD3) region that covers the time span from 2001 to 2018. PADD3 as defined by the Petroleum Administration for Defense Districts (PADDs - EIA, 2012), covers Texas, Louisiana, New Mexico, Alabama, Arkansas, and Mississippi. The region is an important location for refineries as in 2018, 38 out of the 56 US refineries were located in the Texas and Louisiana Gulf Coast region (EIA, 2019b). The oil input data is obtained from EIA (2019b).

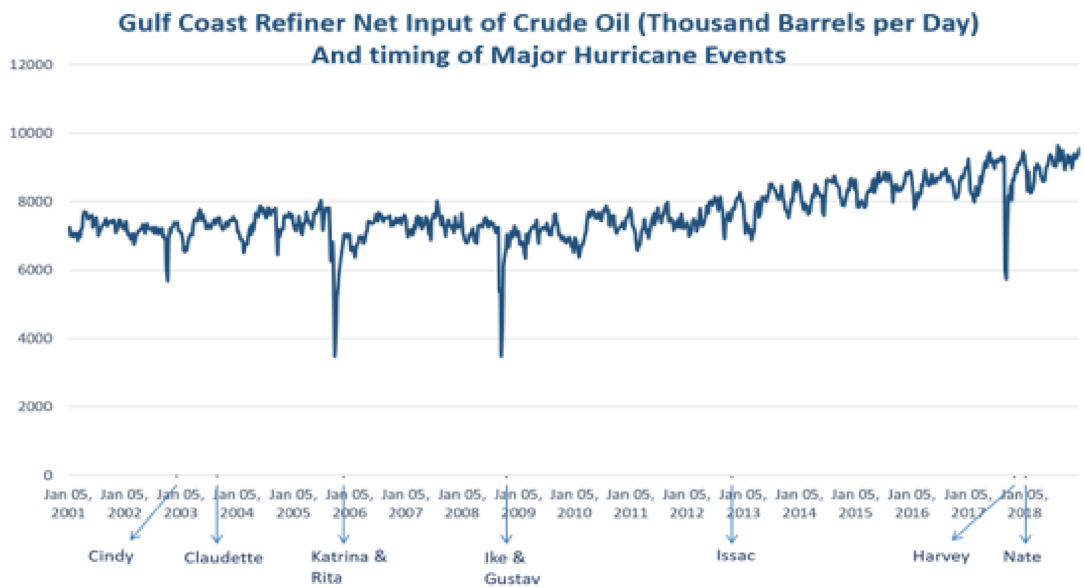

Figure 2.1 Time series of weekly oil input to refineries in PADD3

The reason why we use the refinery input (crude oil) supply instead of output (e.g. gasoline) is that the input is mostly influenced by wind while the output is mostly disrupted by the rainfall and flooding according to an expert working in the oil industry in Houston, Texas. When the wind speed is high, offshore crude oil production often ceases due to unsafe operating conditions, and crude oil imports via barges are affected by closed ports because of unsafe shipping conditions.

2.3.2. Hurricane Characteristics

The hurricane characteristic data we use are forecasts instead of strike data. This is because our fundamental assumption is that those refineries and crude oil suppliers will make operational decisions before hurricanes strike as it takes time to implement decisions thus relying on forecasts. Many previous news reports show support for this assumption. For instance, CNN news reports indicate refineries in the Corpus Christi region shut down in anticipation of a direct hit from Hurricane Harvey in 2017 (Disis et al., 2017). Also, an NPR news report says refineries in the Houston area shut down ahead of Hurricane Ike in 2008 (Housley, 2008).

The hurricane characteristics data we use cover two things: forecasted hurricane strength and forecasted first landfall location. We discuss these individually next.

2.3.1.1. Hurricane Strength

The Saffir-Simpson Hurricane Wind Scale (SSHWS) is used herein to describe the hurricane strength. This scale classifies hurricanes into one of five categories (from 1 to 5, where 1 is indicates the lowest level of strength and 5 indicates the highest level). This indicator is established based on the sustained wind speed (Table 2.1). Also, tropical storms and depressions are also a possible influence on the industry and are defined when conditions preceding a hurricane exist but sustained wind speeds do not reach the lowest level of hurricane strength covered in the SSHWS indicator. Collectively tropical depressions, tropical storms, and hurricanes are called tropical cyclones. (NOAA, 2019a)

We use historical hurricane SSHWS category forecasts issued by National Oceanic and Atmospheric Administration (NOAA) National Hurricane Center (NHC). These data contain information on forecast SSHWS category at different future times, such as what are the forecast storm characteristics 24-hours from the time the forecast is issued, 36-hours out, 48-hours out, and 72-hours out. For example, a 48-hour forecast tells us the probability distribution of the hurricane falling into each of the SSHWS categories in the next 48 hours. We use the strength category with the maximum probability as the forecast category for each time horizon.

Table 2.1 Saffir-Simpson hurricane wind scale

Category	Wind Speed (miles per hour)
Five	≥ 157
Four	130–156
Three	111–129
Two	96–110
One	74–95
Tropical storm	39–73
Tropical depression	≤ 38

Figures 2.2 displays the observed amount of oil inputs to PADD 3 refineries distribution versus the SSHWS hurricane category forecast as it varies across the four forecast windows. The vertical axis is the same in each of the four figure panels and is

oil input per day in thousand barrels. The horizontal axis shows the five SSHWS hurricane categories, where 0 represents conditions where there is no hurricane or tropical storm in the forecast, H0 represents conditions where there is a tropical storm in the forecast, and H1 - H4 represent days when the forecast is for a storm of a particular SSHWS category. We group the H1 and H2 cases because there are very few observations falling into those two categories. H5 is omitted as there were no such forecasts in our data. Generally, the oil refinery input data show as forecasts indicates higher and higher categories, the oil input falls across all of the forecast horizons excepting for the 72-hour forecast where the mean oil input in H3 is a little higher than that in H1and2. Also notice that there are no data for the H4 case in 72-hour forecast window since the data do not show such a case.

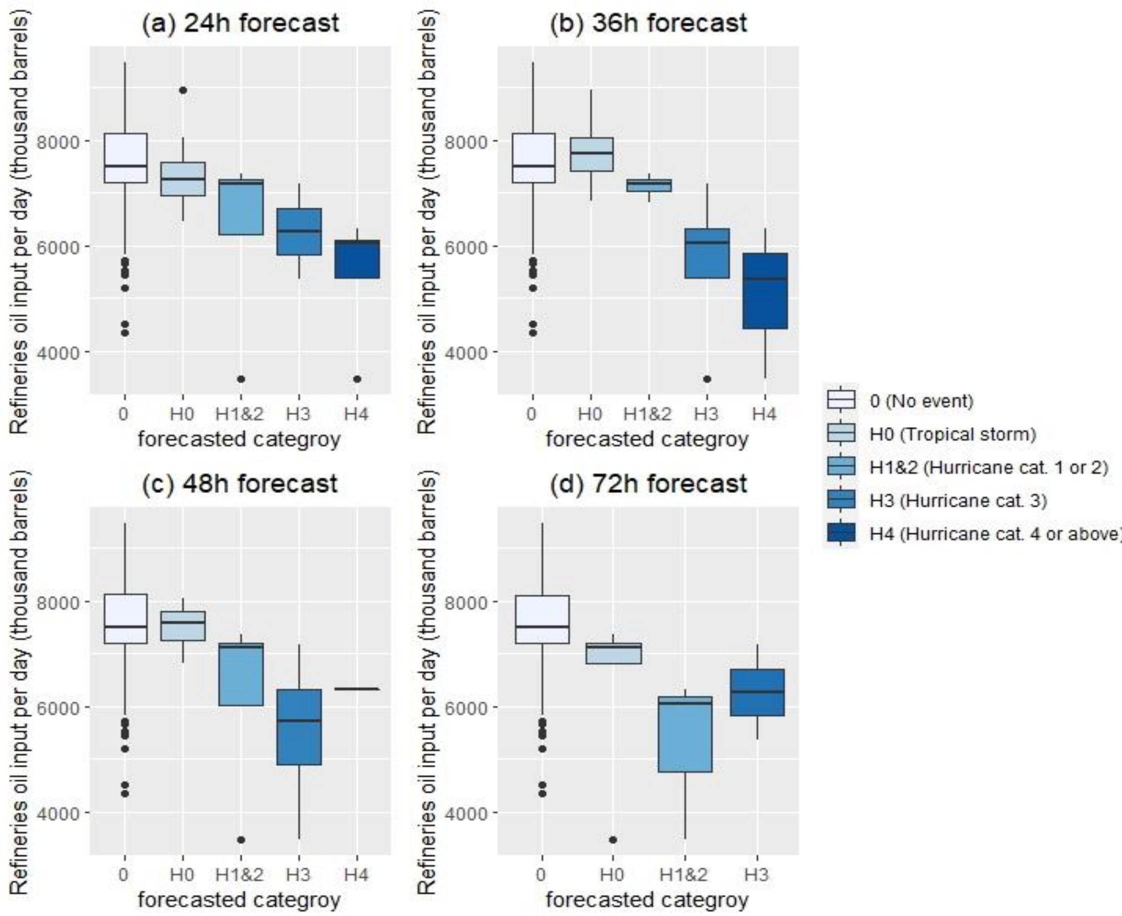

Figure 2.2 Box and whiskers plot of PADD 3 total refinery oil input as it corresponds to different levels of Saffir-Simpson scale forecast strength by time window

2.3.1.2. Hurricane Landfall Location

The impact of hurricanes on refineries not only depends on the hurricane strength but also on proximity of the hurricane path. Hurricanes landing in the Corpus Christi area may not influence refineries in and around New Orleans causing them to shut down, while hurricanes close to New Orleans may not affect activity in Corpus Christi. Since we do not have oil input data by refinery but rather only for the whole Gulf Coast region, we add information of the proportion of the refinery capacity that is located in the forecasted strike region (Figure 2.3). We do this because we anticipate that storms threatening regions with higher capacity share will be more influential than those that threaten lower capacity sub-regions. To do this we define four sub-regions on the Gulf Coast (Figure 2.3). We use the names Corpus Christi area, Houston-Galveston area, Beaumont-Port Arthur area, and the New Orleans-Baton Rouge area for these sub-regions.

To calculate the refinery capacity share by sub-region, we first identified the location of the 38 PADD3 refineries along the Gulf Coast within an ARCGIS map. Then we examined the resultant map and defined our four sub-regions along with the total capacity of refineries located in each sub-region based on data from the 2018 EIA refinery capacity report (EIA, 2018b). We then computed regional capacity shares by taking the ratio of regional capacity to total PADD3 capacity. The resultant refinery capacity shares for the four areas are Corpus Christi 11%, Houston-Galveston 31%, Beaumont-Port Arthur 29%, and New Orleans-Baton Rouge 29% (Figure 2.3). With these four shares, we then compute the affected share based on the forecast strike envelope for a storm. For example, if Corpus Christi and Houston-Galveston fall in the forecast landfall area then we would compute the affected share as 42% (11% + 31%).

In terms of defining the regions in the forecast landfall area we use the NHC hurricane warning and tropical storm warning area (NOAA, 2019b). Here we look at the map of the warning areas and include all of our 4 sub-regions that the storm area on the map covers.

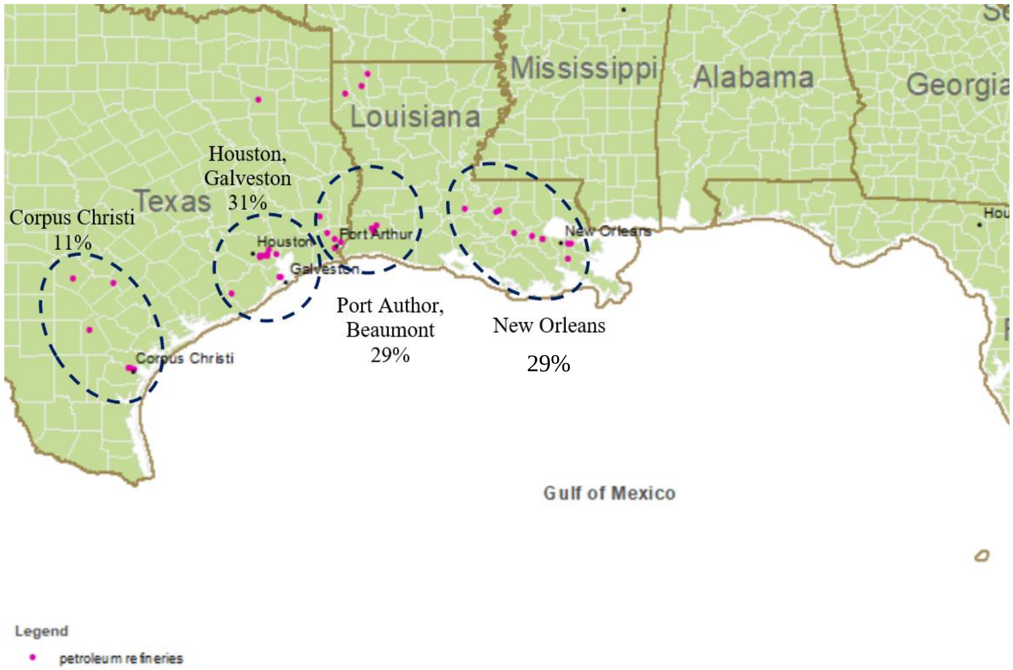

Figure 2.3 Four groups of refineries with their capacity shares

2.4. Methods

Our main goal is to look at damages that hurricanes and their forecasts cause within the energy industry. To do this we will explore the relationship between refinery oil input and hurricane characteristics. We do a regression with weekly oil input as the dependent variable and forecast hurricane characteristics as independent variables along with other factors. The hurricane characteristic data include hurricane strength and affected share of refinery capacity in the forecast landfall area. The hurricane strength measure is the assigned Saffir-Simpson wind scale index. We use dummy variables to represent the forecast incidence of each hurricane category (H1, H2, H3, and H4) or tropical storm (H0) forecast excepting Category 5 as there were no Category 5's in our data. The base is a week without any hurricane or tropical storm forecast (i.e. sustained wind speed <= 39 miles per hour). As mentioned in Data, forecast hurricane category has different time horizons (windows), 24-hour, 36-hour, 48-hour, and 72-hour forecast, indicating the forecasted hurricane category at the landing location before the associated time. Thus, in our regression, we use these for time horizons' forecast in four specifications.

In addition to strength and affected share, we control for several other factors. We observe there is regular ups and downs in Figure 2.1, which due to the seasonality. Also, the gradual uptrend in the oil input was also noted. Thus, we first decomposed the time series of data to see whether we could find trend or seasonal factors using a basic additive time series model (Hyndman and Athanasopoulos, 2018). Stylistically this assumes the time series consists of three components as follows:

$$y_t = T_t + S_t + R_t$$

where T_t is the trend component

S_t is the seasonal component

R_t is the remaining component.

The trend component T_t is obtained by using moving average of the symmetric windows at time t. Seasonal component S_t, is then computed by averaging, for each time unit (week in this case), over all periods, after removing the trend component. Then the remaining component is the portion left after taking out trend and season components from the original data (Hyndman and Athanasopoulos, 2018).

We choose additive model over multiplicative model because multiplicative model is more appropriate when the variations in the seasonal pattern or around a trend are proportional to the level of the time series (Hyndman and Athanasopoulos, 2018), meaning that the spread-out the of data varies across the seasonal pattern or around trend. We check the stationarity using the augmented Dickey-Fuller (ADF) test and find that the data is stationary, further indicating the mean and variance of data are constant over time, and thus additive model is more appropriate.

Figure 2.4 shows the decomposition of additive time series of the refinery oil input from 2001 to 2018 using weekly data. The estimated trend captures the gradual increase of the oil input in those 18 years. The 18 years' refinery oil input shows a general uptrend, and the upward tendency is especially obvious since 2010. The two dips in the trend may be due to the long time to recover from Hurricanes Katrina and Rita in 2005 as well as from Hurricanes Ike and Gustav in 2008. The seasonal component exhibits with the same up and down pattern each year indicating a seasonal effect exists. The remainder figure shows three major decreases of the oil input happened in August 2005, August 2008, and August 2017, which correspond to the time when Hurricane Katrina and Rita (2005), Ike and Gustav (2008), as well as Harvey (2017) came. Thus, we assume that this remaining pattern could be explained by the hurricane characteristics. Since the effect of the shutdown may last and thus it would take time for the recovery of the production, in addition to the forecasted hurricane strength and affected share, we also add one dummy variable (TC_1w) to indicate the lag effect of the hurricane or tropical storm, where 1 indicates there was a hurricane or tropical storm in the last week, while 0 indicates no such event last week.

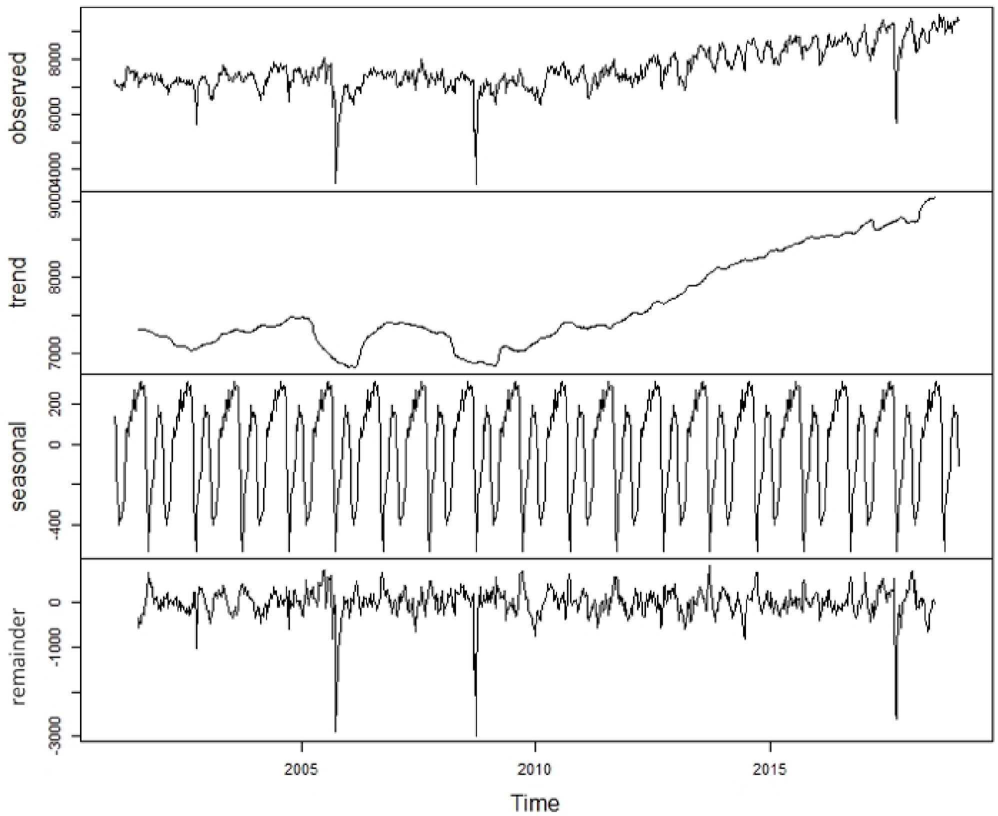

Figure 2.4 Decomposition of additive time series of oil input

To capture these components, our estimated model is:

$$y_t = T_t + S_t + R_t$$

$$\widehat{R}_t = \beta \mathbf{X}_t + e_t$$

where y_t is the refinery oil input in PADD3 in week t,

R_t is the remainder component,

$\mathbf{X}_t$ is a vector of hurricane characteristics including the forecasted hurricane strength and affected capacity share in week t as well as the lag effect variable,

e_t is a White noise error term.

In this model, we first use a time series decomposition that yields the remainder component (R_t) by removing the trend and seasonal components. Then we fit a model using generalized least squares (GLS) since the error term are correlated due to the time series data.

2.5. Results

The relationship of the forecasted hurricane category in different time horizons and the oil input to refineries in Gulf Coast region are preliminarily shown in Figure 2.2, where shows higher the forecast category accompanied with more reduction in the oil input to refineries. To further explore their correlation, time series decomposition model and GLS model are used. Results from the model using GLS are summarized in Table 2.2 and visualized in Figure 2.5.

Table 2.2 presents the results from four specifications that vary in terms of which forecast time window is used: 24-hour, 36-hour, 48-hour, and 72-hour forecast windows respectively. The numbers in the tables are the estimated coefficients for the corresponding variables, while the numbers in parenthesis are the standard errors and the asterisk represent significance level. Log-likelihood as well as Akaike Inference Criterion (AIC) and Bayesian Inference Criterion (BIC) are also presented for each specification.

We find that specification using the 36-hour forecast window, exhibits the best fit among these four. It has the highest log-likelihood and the lowest AIC as well as BIC.

Looking to hurricane related significance, we find regardless of forecast horizon that hurricanes of category 3 or greater and affected share show significant results with a negative sign. Lower categories and tropical storms forecasts are uniformly insignificant. These results indicate high strength hurricane forecasts are associated with oil input reduction.

Also notice that all the coefficients of affected share in the estimations for all four forecast windows are negative and statistically significant at 0.01 level. This is consistent with our expectation that the more capacity that is threatened the larger the oil input reduction. We also find that the coefficients for the lag effect TC_1w, which indicates whether a hurricane forecast happened a week ago, are significant and negative. This indicates that it takes time to restart operations after a forecast has caused an operational reduction in the form of lower oil input.

Figure 2.5 explores the results further showing the estimated effect of hurricane strength in four different forecast windows. The y-axis represents the PADD 3 total refinery oil input (in thousand barrels) after adjusting for trend and seasonality. Notice that the values on the y-axis are all negative indicating hurricanes have a negative effect on the oil input. The x-axis shows the effect of different hurricane strengths, from tropical storm (H0) to Category 4 (H4). As mentioned above, we group hurricane Category 1 (H1) and Category 2 (H2) because there are not enough observations in the data. We can see generally, the higher the forecast hurricane category, the more the oil input reduction. Notice that some of the effects are insignificant (details can be viewed in Table 2.2) but are still plotted for comparison. For instance, the effect of tropical storm (H0), is not very consistent with others since it shows positive in the 24-hour forecast, but this effect is not statistically significant (see Table 2.2). Generally, lower category of hurricane and tropical storm tend to be statistically insignificant. Whereas major level hurricane (category 3 or above) are all statistically significant in all time windows. Notice that the Figure 5(d) does not show H4 due to no observation category 4 forecasts in the 72-hour forecast window within our data.

Table 2.2 GLS results

	Dependent variable:			
	Oil input remainder			
	24h	36h	48h	72h
share1	-895.070***	-645.795***	-726.121***	-901.708***
	(137.712)	(98.298)	(88.782)	(79.245)
h24H0	135.433			
	(88.921)			
h24H1&2	-145.059			
	(118.941)			
h24H3	-332.836**			
	(139.540)			
h24H4	-494.796***			
	(145.412)			
h36H0		-56.493		
		(92.017)		
h36H1&2		4.235		
		(93.040)		
h36H3		-585.228***		
		(114.894)		
h36H4		-889.433***		
		(117.936)		
h48H0			-181.655*	
			(93.817)	
h48H1&2			-397.707***	
			(95.810)	
h48H3			-523.245***	
			(101.824)	
h48H4			-529.965***	
			(179.177)	
h72H0				-127.526
				(87.459)
h72H1&2				-432.716***
				(114.693)
h72H3				-362.320***
				(126.551)
TC_1w	-342.005***	-335.318***	-364.319***	-364.184***
	(42.411)	(41.344)	(42.403)	(43.005)
Constant	19.897	20.033	22.162	21.922
	(26.501)	(26.747)	(27.031)	(27.082)
Observations	887	887	887	887
Log Likelihood	-5,974.993	-5,960.331	-5,978.698	-5,992.426
Akaike Inf. Crit.	11,967.990	11,938.660	11,975.400	12,000.850
Bayesian Inf. Crit.	12,011.010	11,981.680	12,018.420	12,039.100

Note: *p<0.1; **p<0.05; ***p<0.01

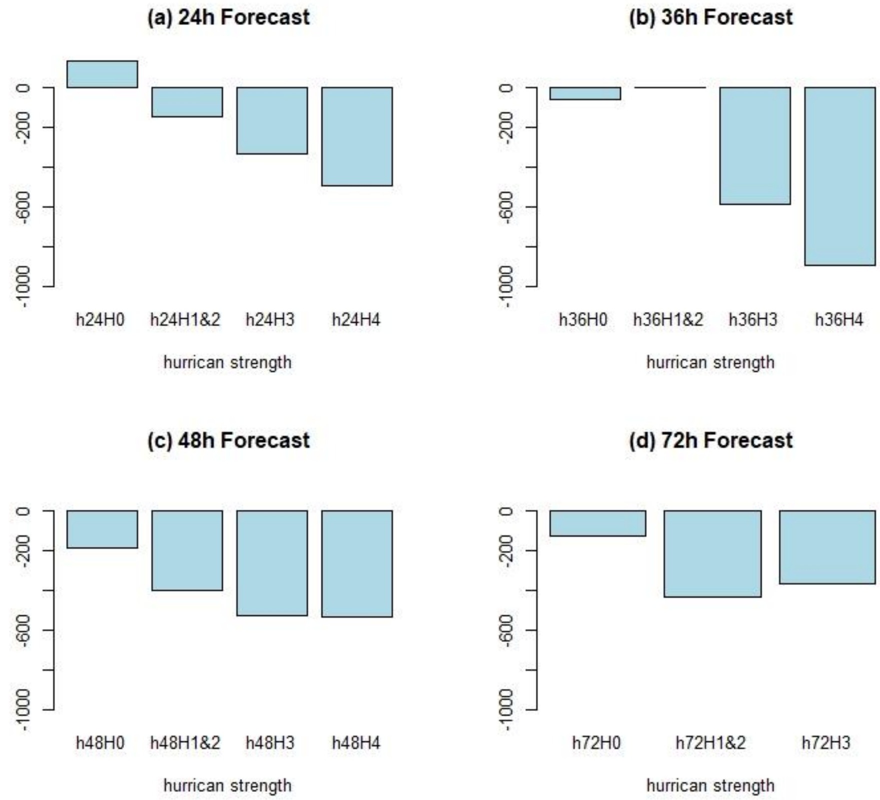

Figure 2.5 The estimated effect of hurricane strength in different forecast windows

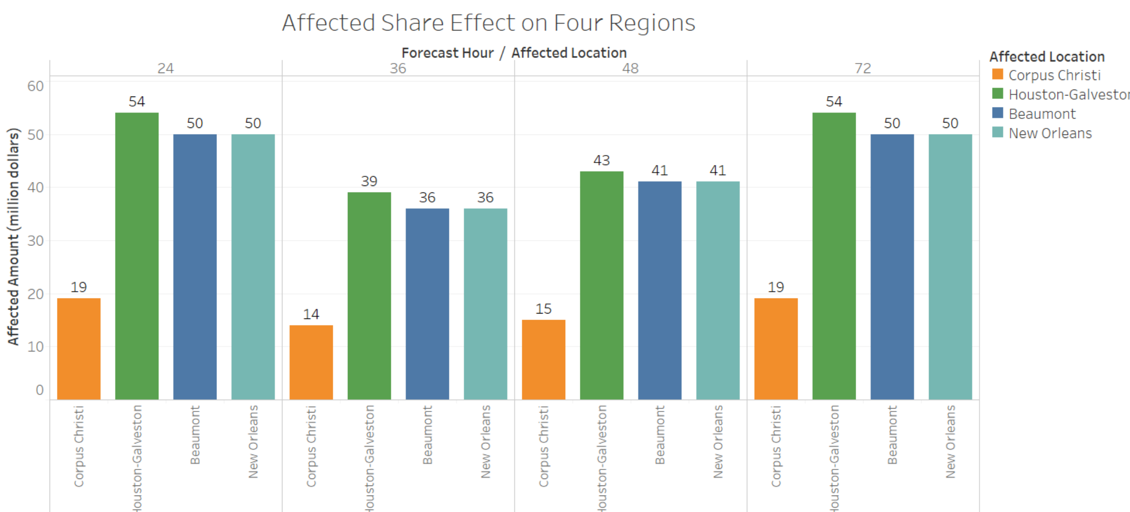

Figure 2.6 Affected share effect on four regions

Figure 2.6 shows the affected share effect from the regression model on four regions based on their share of their refineries' capacities (Corpus Christi 11%, Houston-Galveston 31%; Beaumont-Port Arthur 29% and New Orleans-Baton Rouge 29%). These affected share effects are calculated for 2 weeks, the week of hurricane event and the following week which is influenced. We can see clearly Houston-Galveston has the largest affected amount in all four forecast horizons because it has the largest share (31%). Corpus Christi has the smallest affected amount due to its smallest share among the four regions (11%).

2.6. Discussion

2.6.1. Alternative Methods

In this work, we used additive decomposition model to analyze the effect of hurricane on the refineries' operations. Before we applied the additive decomposition model, we tried different methods and models, one of which worth mentioning was the autoregressive integrated moving average with exogeneous variables (ARIMAX) model. The exogeneous variables, which are the characteristics of hurricane forecasts in our case, are the focus. We first checked the stationarity of the time series of the oil input. Then we determine the order (number of lags) for the ARIMAX model (p, d, q), where p represents the order of the autoregressive model, d represents the degree of differencing, and q represents the order of moving average model, through the auto-correlation function (ACF) and partial auto-correlation function (PACF), and get order of (1, 0, 0) which is also called AR(1). We did not end up choosing this model as our method mainly because of two reasons. First, the ARIMAX model does not directly control for trend and seasonal effects; and second, the loglikelihood measure of model fit for the ARIMAX model is less than that for the decomposition model, while the Akaike information criterion (AIC) of the ARIMAX model is greater than the decomposition model. All indicate that our decomposition method model better fits the data than does the ARIMAX.

The decomposition model results, as mentioned above, shows greater major hurricane category forecast is associated with greater oil input reduction.

2.6.2. Economic Loss

Now let us estimate the economic loss associated with the operational adjustments that led to lower oil inputs. To estimate that loss we need a rough measure of the change in refinery output. To do this we use the so called 3:2:1 crack spread procedure (EIA, 2012). That 3:2:1 crack spread procedure approximates product yield from a typical U.S. refinery. This assumes that for every three barrels of crude oil input, the refinery produces two barrels (42 gallons per barrel) of gasoline and one barrel of distillate fuel which we will treat as equivalent to diesel. Then using the price of those items, we calculate the estimated output sale loss per day. Notice that, the prices may go up due to the short supply of the oil input from the Gulf Coast region, but it is also possible that the increased prices will be pulled down by more supply from other regions. Here for illustration and simplicity, we assume the prices are constant for reference. We use the Gulf Coast conventional gasoline price and the Gulf Coast ultra-low sulfur diesel price drawn from EIA (2020): This results in the formula

Estimated output sale loss per day = (Gulf Coast conventional gasoline price $\times \frac{2}{3} \times 42$

$$+ \text{Gulf Coast ultra-low sulfur diesel price} \times \frac{1}{3} \times 42)$$

$$\times \text{ reduction in oil input in barrels/per day}$$

For example, other things being equal, given a 36-hour before landfall forecast of a category 3 hurricane, refinery oil input is estimated to drop by 523,245 barrels per day. In this case, the estimated output sale loss using the average price computed over August 2010-2019 prices ($2.28/gallon for gasoline and $2.36/gallon for diesel) will be $51M per day and $357M for the event week. Taking account of the lag effect (TC_1w), which would lead to oil input reduction of 364,319 barrels per day in the next week, so the estimated output sale loss would be $35M per day and $245 for the lag week. Thus, the total loss of output sale for this hurricane event for the affected two weeks would be $602M. Similarly, with a 36-hour forecast of a category 4 or above hurricane, the estimated oil input reduction will be 889,433 barrels per day, which will lead to approximately $86M output sale loss per day, and thus $847M for the whole event considering lag effect as well, if everything else is constant.

We can also estimate the effect of the affected share using this estimation equation. Using the equations associated with the 36-hour forecast, as an example, we can find that a 20% increase in the affected share (the approximate difference between corpus and the other areas) will be accompanied with reduction of 129,158 barrels in oil input, which could lead to $12.5M output sale loss per day.

Furthermore, this affected share effect also implies that the inaccuracy in hurricane forecasts may result in additional output sales losses. For example, if a hurricane was forecasted to go to the direction of Houston-Galveston area (share is 31%)

but eventually only affected Corpus Christi (share is 11%), then the forecasted affected share and associated loss would be 20% more than if the forecast had correctly identified corpus Christi along with the lost in corpus Christi due to an strike from a storm that the 36 hour forecast said would not arrive. This additional 20% affected share would be estimated to lead to $12.5M output sale loss per day. The effect of the incorrect forecast could be explored more in the future work.

2.6.3. Operating Profit Loss

Economic loss has been addressed above, but the industry would be more interested in the how their profits would be affected. To estimate the affected profit, refining costs need to be subtracted from the potential revenue that could have been earned without hurricane events.

Refining process converts crude oil to gasoline and diesel. So, the operating profit could be obtained through:

$$\begin{aligned}\text{Estimated profit loss per day} = \ &(\text{Gulf Coast conventional gasoline price} \times \tfrac{2}{3} \times 42 \\ &+ \text{Gulf Coast ultra-low sulfur diesel price} \times \tfrac{1}{3} \times 42 \\ &-\text{Crude oil price/barrel} \\ &-\text{Refining cost of gasoline/barrel} \\ &-\text{Refining cost of diesel/barrel}) \\ &\times \text{reduction in oil input in barrels/per day}\end{aligned}$$

Typical refining costs producing these two products are $0.60 per gallon for gasoline and $0.49 per gallon for diesel (What Determines Retail Prices for Gasoline and Diesel, 2016). Continuing our example in the above part, given a 36-hour before landfall forecast of a category 3 hurricane, we would get operating profit loss of $140M on the event week and the lag week.

2.6.4. Price Change

Notice that when estimating the economic loss and the operating profit loss, we used the fixed prices that were calculated from averaging the past years of August prices as references for illustrative reason. We used monthly prices for August because August is the month when hurricanes come frequently. Using August prices may capture some of the effects of hurricanes on prices, but since they are monthly prices and are averaged across past years, the price increase, if there is any, brought by the short supply due to hurricane cannot be fully reflected. This increase in prices will to some extent make up the loss in the producer surplus result from short supply.

2.7. Conclusions

Energy facilities on the U.S. Gulf Coast are vulnerable to hurricanes. With climate change, this impact may become more severe in the future. This study explores the economic impact of the hurricane characteristics on refinery oil intake in the US Gulf Coast region. To do this we estimate a relationship using generalized least squares applied to the residuals after removing trend and seasonal effects. The estimation is done using EIA data on amount of oil input entering refineries from 2001 - 2018. The results indicate that forecast of stronger hurricanes (Category 3 and above) cause reductions in oil input and thus refinery operations. We also find that oil input falls with increases in the capacity that falls within the forecast strike zone. Moreover, given a 36-hour forecast of a category 3 hurricane we estimate associated output sale losses to be

$51M per day over the strike week plus $35M per day in the a recovery period. Furthermore, our output sale loss estimation also shows that forecast inaccuracy in terms of strike region would increase revenue loss.

There are some limitations of the study. First, in addition to hurricane strength and affected share, other factors like precipitation amount may also be important as it affects refinery output processing. Future study may improve the model by adding forecast precipitation data.

Second, we use four forecast windows individually and not in terms of days before the actual strike. This means that our study is static rather than dynamic. In other words, using these four forecast windows separately in four different specifications and not differentiating them on how near they are to the strike does not allow us to examine the effect of changes in forecast category over time plus the increasing certainty of the information as the strike draws near. Adding more work on dynamics may improve the estimation although the low level of hurricane incidence limits our ability to add many more variables.

The study was also hampered by our inability to obtain more regionalized data (for instance, industry level data) as we desired to study effects in our four areas of being in or out of forecasts and the actual location of the strike. Obtaining and using such data would provide additional insight.

Finally, our economic analysis was not very sophisticated and would be improved by taking into account of the different lengths of lag effect loss from different categories of hurricane, operating costs of the refineries during the affected weeks, as well as losses resulting from the inaccuracy forecast if there is any. Also, the economic loss estimation can also involve a price change, and future study could estimate the loss from consumer surplus's perspective as well.

3. THE ECONOMIC IMPACT OF HURRICANES ON OFFSHORE OIL AND NATURAL GAS OPERATIONS

3.1. Introduction

Offshore oil and gas production in the Gulf of Mexico is an important part of the U.S. energy system. Gulf based offshore crude oil production accounts for 17% of total U.S. crude oil production, and 5% of natural gas production (EIA, 2019a). Moreover, regional offshore production has been increasing in the past years. From 2005 to 2015, it grew by 6.5% (EIA, 2016). More from 2017 to 2019, the Gulf of Mexico crude oil production increased from 1.65 million barrels per day to 1.8 million barrels per day or 12.5 % (EIA, 2017, 2018, 2019c). Though production dropped in 2020 during the coronavirus pandemic, it is expected to increase in the future. (COMMODITIES, 2021)

However, this region is vulnerable to extreme weather events like hurricanes. Historically, many of the large monthly declines in U.S. crude oil production are associated with hurricanes. For example, Hurricanes Gustav and Ike in 2008 caused offshore crude oil production to decrease by more than 1 million barrels per day (EIA, 2019b). Similarly, in 2005, Hurricanes Katrina and Rita caused the shutdown of substantial offshore production with operations not fully recovering for more than six months (EIA, 2019b). Additionally, according to IPCC AR5 (Wong et al., 2014), climate change is expected to increase the intensity of tropical cyclones/hurricanes (increasing precipitation rates, and maximum wind speeds) although their frequency is likely to remain unchanged or decrease. Projections are for substantial industry damages. For example, the Energy Report (Zamuda, 2013) from the Department of Energy (DOE) says the economic impacts of storms and sea level rise on the U.S. Gulf Coast energy industry could reach $8 billion per year by 2030.

These economic impacts are mainly attributed to physical damages to energy infrastructure and business interruption, with business interruption such as operation/production shutdown and crude oil supply decreases accounting for a substantial portion. When hurricanes occur, offshore platforms and rigs, which are large structures that float with an anchor or are fixed to the seabed are vulnerable. They house facilities for well drilling, production and partial processing of produced crude oil and natural gas. But when hurricanes threaten those structures are evacuated for the sake of safety with production interrupted. In turn this affects oil and gas production. For example, two-thirds of the economic losses in the energy industry during 2004 Hurricane Ivan were due to interrupted operations (Zamuda, 2013).

The magnitude of the historical and projected damages arising under this situation makes it important and urgent to explore hurricane impacts on the industry, and here we study the effects on offshore operations.

The chapter contains several sections. The first presents a literature review on the economic impact of hurricanes on the energy sector. Section 3 describes the data used in the study. Section 4 introduces the regression model used and explains why it was chosen. The estimation results are presented in Section 5. Then section 6 contains more discussion and an estimation of economic impact. In the last section (Section 7), we summarize the conclusions and reflect on limitations of the study.

3.2. Literature Review

This study examines the economic impact of hurricanes on offshore crude oil and natural gas production and operation. Our exploration of the previous literature covers three main individual aspects 1) broad studies on the economic impact of hurricanes; 2) studies on the implications of hurricanes for components of the energy sector; and 3) studies on the hurricane impacts on the economics of the energy sector.

3.2.1. Economic Impact of Hurricanes

Many studies have addressed the economic impact of hurricanes. Some have constructed estimates at a macro level, addressing indicators such as GDP (Nordhaus, 2006), economic growth rate (Strobl, 2011, 2012), distribution across multiple economic sectors (Petterson et al., 2006), and regional economy impacts (dominant industries, employment, population, income level, etc. - Coffman and Noy, 2012). Others study the economic impact on a specific sector or industry like the agricultural sector (Chen and McCarl, 2009), business sector (Burrus Jr et al., 2002; Gordon et al., 2010; Zhang et al., 2009), energy sector (Fink et al., 2010; Reed et al., 2010), and tourism (Coffman and Noy, 2012). However, we could not find studies that have targeted effects on offshore entities.

3.2.2. Energy System Impacts

The extent of energy system vulnerability to hurricanes differs between onshore and offshore facilities. Onshore impacts involve infrastructure damage, power outages, and business interruptions all potentially caused by high winds and flooding. Offshore impacts involve platform and pipeline damage or destruction, mostly caused by intense winds and storm surges.

To better understand hurricanes' offshore impact, we review literature addressing hurricane impacts on offshore infrastructure and operation. Those studies address a number of different impacts. Among them, many address vulnerability from a structural and technical perspective. Wisch (2006) assesses the impact of hurricanes on deep-water facilities. Cruz and Krausmann (2008) review the damage caused by Hurricanes Katrina and Rita on the offshore oil and gas industry and identify lessons learned from it proposing adaptation recommendations. Kaiser and Yu (2010) assess structural damage (like destroyed platforms) that was observed in Hurricanes Gustav and Ike in 2008. They also analyze the redevelopment decision making process and predict the redevelopment rate. They assert that redevelopment is likely to happen if the value of remaining reserves is estimated to be greater than cleanup and redevelopment costs.

Some studies examine energy sector vulnerability to extreme weather and climate change in a general and broad way. For instance, Burkett (2011) explores how climate and climate change has affected the offshore operations and production of oil and natural gas. Schaeffer et al. (2012) presents an overview of the impacts of climate change on the energy system. Cruz and Krausmann (2013) analyze the vulnerability of the oil and gas sector to climate change and extreme weather events identifying adaptation and mitigation strategies in oil and gas sector.

Some studies look at the issue from the environmental and hazardous perspective examining effects triggered by hurricanes at offshore oil and gas facilities. Examples include estimates of the costs of oil spills (Pine, 2006) and hazardous-materials releases (Cruz and Krausmann, 2009).

3.2.3. Off Shore Implications

In our literature review we find few studies addressing the economic impact of hurricanes on the offshore production and operation. Some studies explore and analyze the threats of climate change and extreme weather on offshore operation (Burkett, 2011; Cruz and Krausmann, 2013; Kaiser and Yu, 2010; Schaeffer et al., 2012), but very few of them link the hurricane characteristics with offshore production and operation characteristics.

Kaiser (2008), however, does use a regression model to examine the impact of tropical cyclones on offshore hydrocarbon production. The paper estimates the total shut-in production of hydrocarbon caused by tropical cyclones considering hurricane intensity, duration, and path. Kaiser's (2008) paper and our study share the similarity of the linkage to hurricane characteristics, but the main differences between the two are the goal and assumptions. Kaiser's (2008) goal is to estimate the total production shutdown given what actually happened (the number of hurricanes, the observed category of hurricanes, the observed path of hurricanes, and the total duration of hurricanes) in the season.

In our study, one important assumption differentiating feature is that we will examine the extent to which oil and gas production shutdown and rig evacuation depends on the hurricane forecast characteristics, while the ones after the hurricane has passed depend on many other factors like damage magnitude, clean-up, and repair needs.

Due to that assumption, we only focus our shutdown or evacuation rate before the hurricanes estimates . Also, we use shut-in production provided by the Bureau of Safety and Environmental Enforcement (BSEE) as a regressor to see how forecast hurricane characteristics affect shutdown and evacuation proportion.

3.3. Data

To investigate the impacts of hurricanes offshore oil and natural gas production we need data on offshore production and hurricane characteristics. We discuss those items below.

3.3.1. Effects on Offshore Oil and Natural Gas Production

When severe weather systems like tropical cyclones approach to the Gulf of Mexico they create threats for crude oil and natural gas production facilities and structures. As a result, production starts to shut down and personnel on offshore platforms and rigs begins the process of evacuation (BSEE, n.d.). Platforms and rigs refer to the large structures with facilities used for well drilling in order to extract and process crude oil and natural gas, and the main difference between them is that platforms are fixed to the seabed while rigs are movable (The Shipping Law Blog, 2018.) The Bureau of Safety and Environmental Enforcement (BSEE) monitors the situation and creates reports on offshore crude oil and natural gas production shutdowns as well as platform and rig evacuation on a daily basis. Since the total number of offshore production facilities has changed during 2001 - 2018, we use the shutdown proportions rather than the absolute count. Similarly, we use evacuation proportions rather than total number.

One thing that needs to be pointed out is that platform recovery and return to operation could take days to months. For example, oil and natural gas production shutdowns caused by Hurricanes Gustav and Ike in 2008 took about 6 months to come down to normal levels while those caused by Hurricanes Katrina and Rita in 2005 took about 9 months to recover (BSEE, 2019). However, the length of the recovery time may be influenced by many forces, such as hurricane intensity and duration as well as non-hurricane factors like time needed to complete safety checks. In this study we are focused on how hurricane wind speed directly influences offshore production and operation and try to minimize the effect of other factors by only using the shutdown and evacuation proportions before the shutdown peak.

3.3.2. Forecast Hurricane Wind Speed

The hurricane data we use in this study are forecast data, under the assumption that energy entities make operational decisions based on forecast information. The hurricane forecast data we use arise from the National Oceanic and Atmospheric Administration (NOAA, 2019), and provide the probability distribution of the hurricane category forecast. We also calculate expected forecast wind speed as a weighted average of the median wind speed of each category times the forecast category probabilities.

Before and during a tropical cyclone, NOAA provides storm forecasts at least every 6 hours with different forecast time horizons including 24-hour, 36-hour, 48-hour, and 72-hour, indicating where and how strong the storm would be in the next 24, 36, 48, and 72 hours. To make these data useful to our model, we create a timeline that at a given time has synchronized observations of forecast from all four prior forecasts. In other words, with this transformation we can know what the forecasts were for that time in the relevant prior 24-, 36-, 48-, and 72-hour forecasts. To make those data compatible with the offshore production and evacuation data, we summarize the data into daily expected forecasted wind speed by averaging the 4 appropriate forecasts.

3.4. Methods

Our main goal is to explore whether there is a relationship between the forecast hurricane wind speed and the offshore production shutdowns and evacuations. We examine four different dependent variables (oil production shutdown, natural gas production shutdown, oil platform evacuation, and rig evacuation). Note these dependent variables are all expressed as proportions, ranging from 0 to 1, shown in Figure 3.1. In this case, models with no restriction on the dependent variable like ordinary least squares (OLS) are not appropriate. On the other hand, uses of assumed Beta distributions are flexible and often used for modelling proportional dependent variables, and it allows different density shapes. Here we assume that the dependent variables are beta-distributed, so we use beta regression.

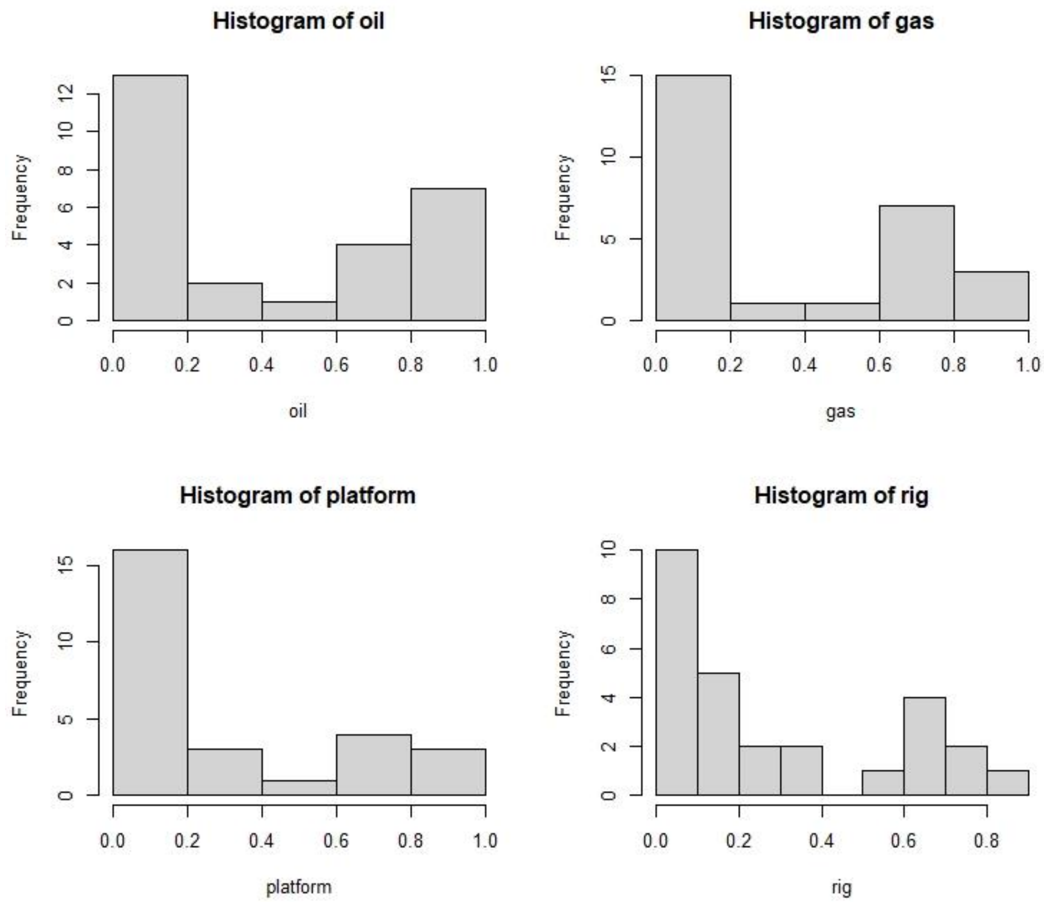

Figure 3.1 Distribution of the dependent variables

The beta regression model was introduced by Ferrari and Cribari-Neto (2004) and is designed for estimation when dependent variables are continuous and limited to the interval (0,1). This beta regression model stems from the typical beta density:

$$f(y; p, q) = \frac{\Gamma(p+q)}{\Gamma(p)\Gamma(q)} y^{p-1}(1-y)^{q-1}, \quad 0 < y < 1,$$

where p > 0, q > 0, and $\Gamma(\cdot)$ is the gamma function. The mean and variance of response *y* are

$$E(y) = \frac{p}{p+q}$$

and

$$\text{Var}(y) = \frac{pq}{(p+q)^2(p+q+1)}$$

Instead of using p and q, the beta regression model proposes an alternative way to parameterize the beta density by setting $\mu = p/(p + q)$ and $\phi = p + q$:

$$f(y; \mu, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} y^{\mu\phi-1}(1-y)^{(1-\mu)\phi-1}, \quad 0 < y < 1,$$

where $0 < \mu < 1$, $\phi > 0$, so that it can easily model the mean of the response:

$$\text{E}(y) = \mu$$

and the variance of y is

$$\text{Var}(y) = \frac{\mu(1-\mu)}{1+\phi}$$

As in our case, we assume the dependent variable y is beta-distributed, so we have $y \sim B(\mu,\ \varphi)$, and the model is

$$g(\mu_i) = X_i^{\text{T}}\beta$$

where X_i is a vector of the expected forecast wind speed over four different time horizons as well as the hurricane threshold which is a dummy variable that indicates whether the forecast wind speed is large enoung to be declared a hurricane; and μ_i is the mean of oil shutdown proportion / natural gas shutdown proportion / platform evacuation proportion / rigs evacuation proportion before peak in these four models respectively.

Notice that $g(\cdot)$: $(0, 1) \rightarrow \mathbb{R}$ is a link function, which could take the different forms, including logit $g(\mu) = \log(\mu/(1-\mu))$; probit $g(\mu) = \Phi^{-1}(\mu)$; log-log $g(\mu) = -\log\{-\log(\mu)\}$; complementary log-log $g(\mu) = \log\{-\log(1-\mu)\}$; and Cauchy $g(\mu) = \tan\{\pi(\mu -$

0.5)}. In our case, logit link is chosen for it has the lowest AIC and/or highest log-likelihood among those link functions.

Given this model we will study whether and how much production interruption or evacuation is affected. To do this, data are collected on four dependent variables giving the proportion of facilities a) that produce crude oil are shutdown; b) that produce natural gas are shutdown; c) that are producing platforms that are evacuated, and d) that are producing rigs that are evacuated. In each model, we have four differing independent variable specifications involving expected wind speed forecast from four different forecast windows, including 24, 36, 48, as well as 72-hour forecast.

3.5. Results

After model comparisons among different link functions used in beta regression, we keep the logit link function results because they have either the highest R^2 and log-likelihood and/or the lowest AIC. The regression results are presented in Table 3.1 – 3.4. The tabled numbers are the coefficients from the beta regression model giving the effects of the windspeed on the dependent variable across different forecast horizons, while the numbers in the parenthesis are their standard error. We can find that generally for oil shutdown rate and gas shutdown rate models, hurricane threshold shows statistical significance in all forecast horizons expect 72-hour forecast. Whereas the forecast wind speed is statistically significant in these two models for 72-hour forecast windows. In modelling the platform evacuation rate, forecast wind speed displays statistical significance in 24 and 72-hour forecast; while in the model of rig evacuation rate, forecast wind speed shows significance in all four forecast horizons.

Table 3.1 Beta regression summary with response of oil shutdown rate

	Dependent variable:			
	Oil shutdown rate			
	(1)	(2)	(3)	(4)
Expected wind speed forecast (24h)	0.022			
	(0.014)			
Hurricane threshold (24h)	1.440^{*}			
	(0.768)			
Expected wind speed forecast (36h)		0.014		
		(0.014)		
Hurricane threshold (36h)		2.443^{***}		
		(0.788)		
Expected wind speed forecast (48h)			0.020	
			(0.014)	
Hurricane threshold (48h)			1.821^{**}	
			(0.759)	
Expected wind speed forecast (72h)				0.043^{**}
				(0.020)
Hurricane threshold (72h)				0.842
				(0.902)
Constant	-2.829^{***}	-2.703^{***}	-2.862^{***}	-3.842^{***}
	(0.917)	(0.870)	(0.839)	(1.196)
R^2	0.326	0.386	0.360	0.338
Log Likelihood	31.033	34.699	32.842	31.673
Akaike Inf. Crit.	-54.066	-61.398	-57.683	-55.345
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			

Table 3.2 Beta regression summary with response of natural gas shutdown rate

	Dependent variable:			
	Gas shutdown rate			
	(1)	(2)	(3)	(4)
Expected wind speed forecast (24h)	0.019			
	(0.013)			
Hurricane threshold (24h)	1.713^{**}			
	(0.682)			
Expected wind speed forecast (36h)		0.018		
		(0.013)		
Hurricane threshold (36h)		2.208^{***}		
		(0.682)		
Expected wind speed forecast (48h)			0.025^{**}	
			(0.012)	
Hurricane threshold (48h)			1.779^{***}	
			(0.653)	
Expected wind speed forecast (72h)				0.041^{**}
				(0.018)
Hurricane threshold (72h)				1.215
				(0.791)
Constant	-3.237^{***}	-3.404^{***}	-3.748^{***}	-4.258^{***}
	(0.841)	(0.798)	(0.774)	(1.096)
R^2	0.291	0.330	0.312	0.292
Log Likelihood	30.874	34.223	33.189	32.070
Akaike Inf. Crit.	-53.748	-60.446	-58.379	-56.140
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 3.3 Beta regression summary with response of platform evacuation rate

	Dependent variable:			
	Platform evacuation rate			
	(1)	(2)	(3)	(4)
Expected wind speed forecast (24h)	0.026**			
	(0.013)			
Hurricane threshold (24h)	0.497			
	(0.655)			
Expected wind speed forecast (36h)		0.018		
		(0.013)		
Hurricane threshold (36h)		1.091		
		(0.681)		
Expected wind speed forecast (48h)			0.019	
			(0.012)	
Hurricane threshold (48h)			1.088*	
			(0.641)	
Expected wind speed forecast (72h)				0.035*
				(0.018)
Hurricane threshold (72h)				0.228
				(0.802)
Constant	-3.142***	-2.820***	-2.934***	-3.487***
	(0.826)	(0.800)	(0.750)	(1.094)
R^2	0.487	0.552	0.572	0.464
Log Likelihood	18.487	19.944	20.467	18.037
Akaike Inf. Crit.	-28.975	-31.888	-32.934	-28.074
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 3.4 Beta regression summary with response of rig evacuation rate

	Dependent variable:			
	Rig evacuation rate			
	(1)	(2)	(3)	(4)
Expected wind speed forecast (24h)	0.031^{**}			
	(0.013)			
Hurricane threshold (24h)	0.086			
	(0.647)			
Expected wind speed forecast (36h)		0.023^{*}		
		(0.013)		
Hurricane threshold (36h)		0.716		
		(0.670)		
Expected wind speed forecast (48h)			0.035^{***}	
			(0.012)	
Hurricane threshold (48h)			-0.018	
			(0.633)	
Expected wind speed forecast (72h)				0.052^{***}
				(0.018)
Hurricane threshold (72h)				-0.732
				(0.782)
Constant	-3.389^{***}	-3.091^{***}	-3.588^{***}	-4.361^{***}
	(0.823)	(0.798)	(0.766)	(1.088)
R^2	0.314	0.321	0.399	0.410
Log Likelihood	21.762	22.953	23.776	22.674
Akaike Inf. Crit.	-35.524	-37.906	-39.551	-37.349
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			

Figures 3.2 – 3.5 present regression results for the four dependent variables: oil shutdown rate, gas shutdown rate, platform evacuation rate, and rig evacuation rate, respectively. Each contains four graphs showing the four different forecast horizons used. The horizontal axis represents the average forecast wind speed, and the vertical axis represents the proportion shutdown or evacuated.

For instance, Figure 3.2 shows the relationship between oil production offshore facility shutdown proportion and the expected forecast wind speed using four different forecast windows from each of the 24h, 36h, 48h and 72h forecasts. Generally speaking, we find the higher the forecast wind speed is associated with larger oil production shutdown proportion across all four forecast windows. Moreover, there is a big jump in the oil shutdown rate when the forecast wind speed rises to 74 miles per hour (mph), which is the threshold for definition of hurricane Category 1. When the expected forecast wind speed is below 74 mph but above 39 mph (the condition for a tropical depression or tropical storm forecast), the oil production shutdown proportion is typically below 25%. Whereas when the forecast wind speed is above 74 mph, the oil production shutdown is at least 60%. Combining the regression results in Table 3.1, we can find that this jump is largely captured by the variable hurricane threshold that we used in the model. This indicates that the oil shutdown rate is mainly associated with the hurricane threshold. In other words, whether there will be a hurricane may play a more important role on the shutdown decision than what wind speed the hurricane will be.

Similar patterns are found in the model with dependent variable of gas shutdown rate, where the hurricane threshold captures the main difference in the natural gas shutdown rate. However, the models for evacuation rate do not show an obvious jump when the forecast wind speed reaches hurricane levels (74 mph). Instead, the curves for those cases are relatively flatter, which is due to the bad high leverage points in statistics, in other words, some observations show high forecast wind speed but low evacuation rates in this case. This flatter pattern is consistent with the regression results in Figure 3.4 and 3.5, where forecast wind speed shows statistical significance rather than hurricane threshold, as we mentioned. With further investigation, we find that this is probably due to two reasons: 1) the evacuation rate for platform and rig indicate the proportion of the platform/rigs that personnel has been evacuated from, and the evacuation rate in our sample is generally less than the oil and gas shutdown rate at a certain expected forecast wind speed; 2) shutting-in oil and gas production is a standard safety procedure, but evacuation is typically subject to mandatory notice, and 3) hurricane path and affected regions may be different.

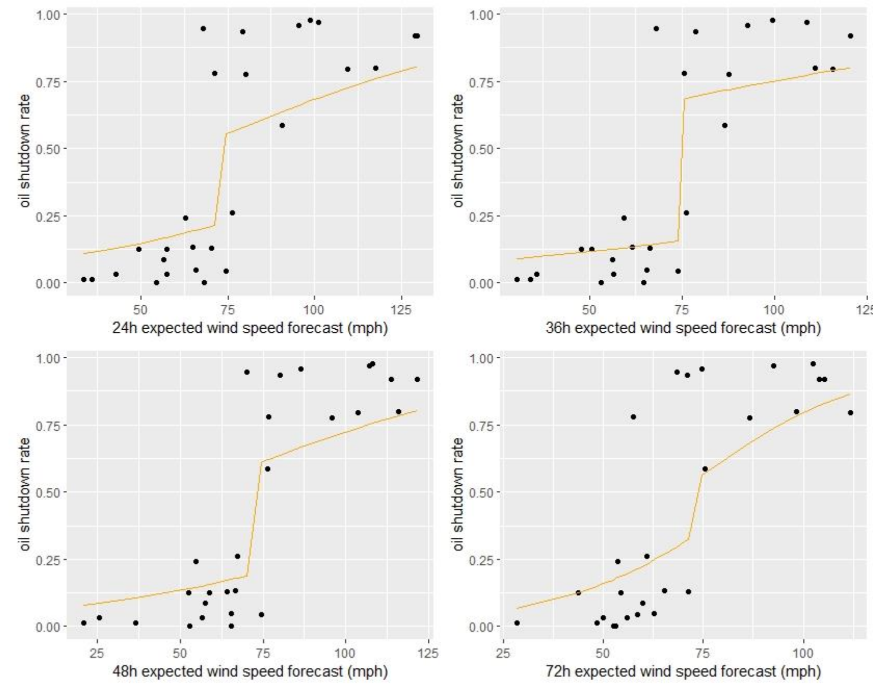

Figure 3.2 Beta regression results with response of oil shutdown rate

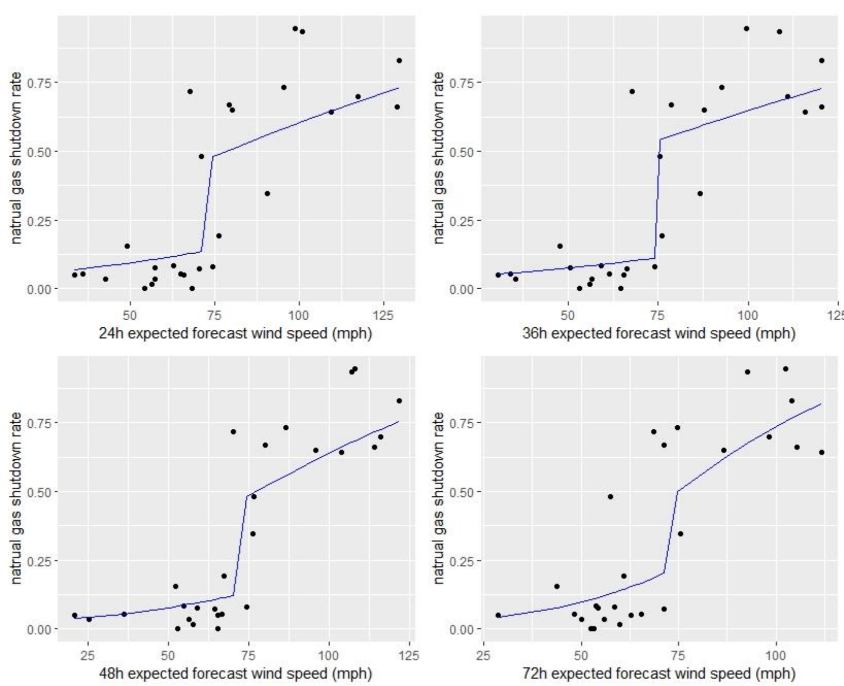

Figure 3.3 Beta regression results with response of natural gas shutdown rate

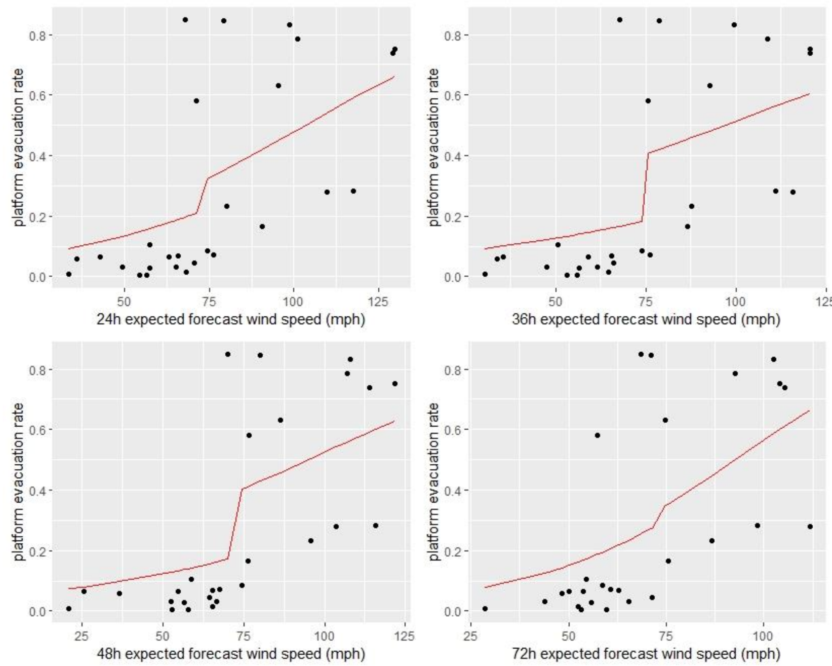

Figure 3.4 Beta regression results with response of platform evacuation rate

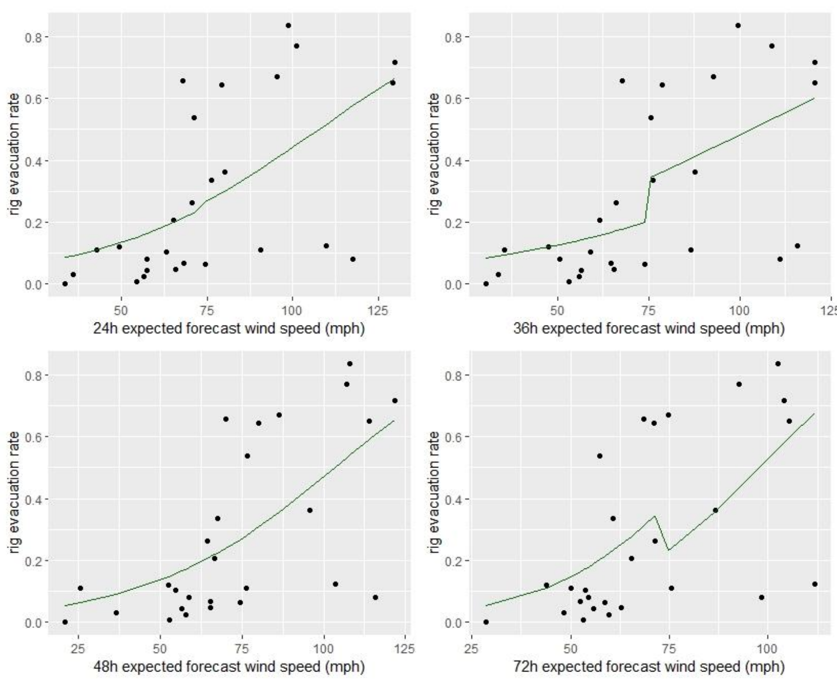

Figure 3.5 Beta regression results with response of rig evacuation rate

3.6. Discussion

3.6.1. Further Interpretation

The beta regression results show two main conclusions: 1) for oil shutdown rate and gas shutdown rate models, effect of hurricane threshold is positive and statistically significant. This indicates that a hurricane forecast is associated with an obvious oil shutdown rate increase; 2) for platform evacuation rate and rig evacuation rate models, the forecast wind speed effects are positive and statistically significant, demonstrating that shutdown and evacuation rates increase with forecast wind speed. The interpretation of the coefficients, however, is not straightforward, but can be analyzed as the following way. For instance, the coefficient of hurricane threshold in the oil shutdown rate model using 24-hour forecast horizon is 1.440, indicating that when there is a hurricane forecast (no matter which category), the log odds of the offshore oil production shutdown rate ($\log(\mu/(1-\mu))$) would increase by 1.440. Therefore, the odds of the offshore oil production shutdown rate ($\mu/(1-\mu)$) would increase multiplicatively by 4.22, demonstrating that the ratio of the rate of shutting down oil production (μ) and the rate of not shutting down ($1-\mu$) would increase 4.22. If the original shutdown rate is 30% (so rate of not shutting down is 70%), then given there is a hurricane forecast, the shutdown rate will become 65% (because 30%/70% × 4.22 ≈ 65%/35%), other things being equal.

Take rig evacuation rate model as another example, the coefficient of expected forecast wind speed using 24-hour forecast horizon is 0.031. This means when expected forecast wind speed increases by 20 mph, the log of the odds of the offshore rig evacuation rate (log(μ/(1- μ))) would increase by 0.62 (0.031 × 20). Accordingly, the odds of the rig evacuation rate (μ/(1- μ)) would increase multiplicatively by 1.86 for every 20 mph increase in the forecast wind speed. In other words, suppose the original shutdown rate is 30% (so rate of not shutting down is 70%), with the expected forecast wind speed increases by 20 mph, the rig evacuation rate will become 44% (because 30%/70% × 1.86 ≈ 44%/56%).

3.6.2. Economic Loss and Profit Loss

Knowing the significant impact, the next issue we need to consider is the economic implication. What does the odds change mean for industry economics? Let's use an example to illustrate. At the hurricane wind speed of category 1 (74 mph), the estimated gas production shutdown rate is 55%, and if the expected forecast wind speed increases by 20 mph to 94 mph, the estimated shutdown rate would be 65%, whose odds is 1.52 times of the odds of 47.8% (because 0.65/(1-0.65) ≈ 1.52 * 0.55/(1-0.55)). Similarly, if the expected forecast wind speed further increased by 20 mph to 114 mph, the estimated gas shutdown rate would become 75% (0.75/(1-0.75) ≈1.52 * 0.65/(1-0.65)).

For economic estimation of the associated damages, we compute the expected volume of production lost times the oil price. We obtain the average offshore U.S. Gulf of Mexico oil production in August (when most hurricane occurs) of the past five years (2016-2020), 1.7 million barrels per day, as well as the average offshore U.S. Gulf of Mexico crude oil first purchase price ($ per barrel) in August in the past five years (2016-2020), $50.78 per barrel, from EIA. Under this assumption, 20 mph increase in the expected forecast wind speed from the threshold of the hurricane Category 1 (74 mph) would reduce about 10% of the oil production, about 170 thousand barrels per day, and therefore lead to roughly $8.6M per day loss of revenue. If use typical operating margin of oil and gas production companies, roughly 15% (Andriy Blokhin, n.d.), then the estimation of the profit loss from oil production shutdown by 10% would be $1.29M per day. Similarly, 10% reduction of the gas production resulting from 20mph increase in forecast wind speed will lead to approximately $800 thousands loss of revenue and thus $120 thousands loss of operating profits.

The above loss estimation focused on the producer surplus change in the Gulf Coast region and used fixed price as reference. From another perspective, there are some concerns on the estimation of the economic estimation here. One concern is that the reduction in the supply of crude oil and natural gas from the Gulf Coast region can be made up by the supply from other region or imports. If consider the producer surplus in whole society, then no economic loss from reduced revenue should be counted. Another concern is that if the supply gets negatively affected, crude oil prices should increase as a response, which will reduce the loss in producer surplus. Both of those concerns depend on more empirical supports and could be further studied as an extension and from a different angel.

3.7. Conclusions

In this essay, we report on a study of the economic impact of hurricanes on offshore U.S. Gulf of Mexico oil and gas production. The study explores the relationship between forecast wind speed and offshore facticity shutdown rate as the evacuation rate for platforms and rigs. Beta regression is used as we assume the dependent variables in all four models are beta-distributed proportions. Results show that the shutdown and evacuation rates rise with an increase in the forecast wind speed and/or with the declaration that a hurricane will occur. The revenue loss on the production reduction of crude oil and natural gas are estimated to be $9.4M per day, with operating loss amounting to $1.4M per day. Also, it is likely that this is a lower bound estimate as the number of offshore facilities is increasing and thus in the future without changes in hurricane characteristics this would likely become larger. Moreover, if the projected climate change influenced hurricane intensity increases come to pass then revenue loss would also increase.

There are several limitations of our study which also suggest possible research extensions. One should notice that the forecast wind speed we use in the study is an expected value, which is obtained by calculating the average of the mean wind speed of each category weighted by the forecast category probabilities. Averaging however, pulls the forecast wind speed to the middle and away from the highest possible speed in the forecast. This may not reflect the wind speed decision makers consider. They may be conservative and plan for a more than average win speed and thus react to a more severe expected threat. Perhaps the model should be estimated with a maximum speed or a form of an upper confidence interval. For instance, if the forecast shows that Category 4 is the most likely category, whose mean wind speed is 143 mph, but the calculated expected wind speed is only 112 mph (Category 3), then the Category 4 wind speed cannot be reflected in our model. This is a common issue when using average values. Future study can improve this by also considering the distribution of the forecast.

Another limitation is that we only include the forecast wind speed as an explanatory variable. In a more realistic world, offshore oil and gas production and operation could be influenced by hurricane path as for example there are more rigs off the Louisiana coast than off the Texas coast. We could again include explanatory variables like percent of facilities in the forecasted path.

Additionally, apart from weather events, some other events like pandemic, political, and economic events may also have influence on the offshore production. This issue, however, is in fact limited by the data we gathered. As mentioned in the Data part, the offshore oil and gas production as well as platform and rig evacuation rates come from BSEE, and these data are only released when there is or will be a tropical cyclone. If we intend to study what and how incidents or weather events may have impact on the offshore crude oil and natural gas production, then continuous data is required. Future study could improve the study through the improved data.

Moreover, further study could also explore the recovery phase from the shutdown, since different recovery times will also alter revenue loss. Furthermore, concerns of the consumer and producer surplus in the whole society as well as the crude oil and natural gas prices change result from decreased supply could also be considered and further studied.

4. THE ECONOMIC IMPACT OF HURRICANE FORECAST ACCURACY ON GULF COAST PETROLEUM REFINERIES

4.1. Introduction

The U.S. Gulf Coast is an important region in the U.S. oil and gas industry (EIA, 2019a). Many petroleum refineries are located in this area. However, this region is vulnerable to hurricanes. In 2017, hurricane Harvey caused the shutdown of approximately 2.2 million barrels per day of refining capacity or roughly 45% of the Texas Gulf Coast capacity (Jacobs, 2017). Also, with climate change, the intensity of hurricane and tropical storms is likely to increase (Kishtawal et al., 2012; US EPA, n.d.).

Refineries and other entities make shut-down decisions based on forecasts. When hurricanes or tropical storms move toward the United States the NOAA National Hurricane Center issues a forecast. In the previous chapters we studied the economic impact of hurricanes on the Gulf Coast oil and gas operations, where found that hurricane forecast characteristics negatively impacts oil input to refineries and offshore activity. However, in doing that we did not consider forecast accuracy. Forecasts are not always perfect predictors of intensity, strike location, and timing. This raises the question, does an inaccurate forecast impose added cost on the refineries? If yes, then how large is that cost and where does the impact come from? This chapter aims to explore and answer these questions.

4.2. Background

Recent experience shows an increase in the impact of hurricanes and tropical storms on the U.S. Gulf coastal region and projections indicate that climate change is likely to further exacerbate this (US EPA, n.d.). This makes the issue of hurricane forecast accuracy an important research area.

Some studies have focused on making better use of models and frameworks as means to improve hurricane forecast accuracy. For instance, in 2008 NOAA established the ongoing Hurricane Forecast Improvement Project (HFIP) to increase the knowledge on vulnerability and to improve forecasts accuracy so as to mitigate the impacts (Gall et al., 2013). Also, Taskin and Lodree (2011) explored ways to improving forecast accuracy through nesting the National Hurricane Center's hurricane prediction model into a Bayesian decision framework.

Hurricane forecasting, however, is not just a meteorological, technical, forecast accuracy problem it is also an economic problem with associated and consequential actions. Societal decisions also involve allocating scarce resources to save lives, reduce economic impact, and invest in research for improvement. Previous literature found that larger errors in the prediction in hurricane landfall location cause higher damage (Martinez, 2020). Also, developing and enhancing hurricane forecasts could be costly. Research and discussion directed toward increasing the economic value of hurricane forecasts can help public officials make decisions on investing in such improvements (Considine et al., 2004). Previous literature covers hurricane forecast economic dimensions in a number of ways.

Some literature analyzes the economics of hurricane or more generally hazard forecasts using willingness to pay approaches. In other words, they study how individuals perceive the need to fund activities to improve hurricane forecasting accuracy (Lazo et al., 2010; Lazo and Waldman, 2011; Nguyen et al., 2013; Mozumder et al., 2015; Park and Yoo, 2018; Ahsan et al., 2020; Rahaman and Iqbal, 2021; Wehde et al., 2021; Molina et al., 2021). For example, Lazo et al. (2010), Lazo and Waldman (2011), and Molina et al. (2021) conducted a survey to analyze household willingness to pay for the improvement of hurricane forecast attributes such as more accurate forecasts of landfall time and location, wind speed, and storm surge. Lazo et al. (2010) found significant willingness to pay for improved information on those items. Molina et al. (2021) found that the highest willingness to pay is for improvements in accuracy on wind speed, followed by the storm track (path) and precipitation (Nguyen et al., 2013; Park and Yoo, 2018). Further study willingness to pay finding similar value is places on accuracy improvement. Study result shows that 3.4% of U.S. economic output variation account for weather variability (Lazo and Waldman, 2011).

Some other studies have addressed the value of improved accuracy by examining effects on the cost of evacuation and the loss from potentially avoidable evacuation. These studies embody an assumption which is used in our study as well: inaccurate hurricane forecasts can improperly assert areas are at risk or overstate risk and in turn cause excessive and costly evacuation. They also assume that could be avoided under improved forecast accuracy. Anderson and Burnham (1973) studied and estimated the potential savings from the reduction of the average forecast error, using a combination of game-theory and decision theory approaches finding that the potential savings to economic sector from reduction of forecast error to one-half of current value would be at least $15.2M in the first year in 1973 U.S. dollars. Considine et al. (2004) studied the value of hurricane forecast for the oil and gas producers through analyzing the costs of evacuation and potential costs of not evacuating, drawing the conclusion that costs decrease as forecast accuracy improves. Similar results were also found by Martinez (2018) that 60% in the improvement in hurricane forecast accuracy is associated with 15% - 30% reduction in evacuation costs.

While the literature reviewed above has studied the economic value of hurricane forecasts, they have generally concentrated on the economic impact to households and the general business sector without a great deal of focus on the multi-billion-dollar oil and gas refining industry. Considine et al. (2004) did examine impacts on offshore oil and gas production and the evacuation of offshore platforms and rigs but not on shore components. Our study will extend that work focusing on impacts to petroleum refineries on shore. To do this we extend the work in the earlier chapter that found hurricane forecast attributes / characteristics have statistically significantly negative impact on oil input to refineries.

4.3. Data

As mentioned, we will examine whether and how, if yes, inaccurate hurricane forecasts would negatively affect decisions on the oil input to refineries and in turn enhanced economic impact. To achieve this, we build upon the model results from essay 1 in chapter 2, which explores the economic impact of the hurricane characteristics on the oil input to Gulf Coast refineries. There we drew the conclusion that both hurricane category forecast and hurricane strike location forecast negatively affect crude oil input to refineries. In particular the higher the forecasted hurricane category or the larger the share of the capacity in the warning region the greater the reduction in oil input (i.e. the more the oil input shutdown). As a result, a further question is raised: What if the forecast is inaccurate? Will the inaccuracy in the forecast cause different decision making on the shutdown of the refineries? What will be the influence of this inaccuracy if there is any? To answer these questions, we need to figure out the difference between the forecast data and the actual outcome, which arises from the observed data we get after hurricanes. Details of our approaches to using the data are in the following section.

4.3.1. Hurricane Characteristics

In the model of Chapter 2, the hurricane characteristic data used are forecasts rather than observed strike data. This is based on our fundamental assumption that refineries and crude oil supplier make operational decisions before hurricanes strike because it takes time to implement decisions. In this chapter, we want to know how the effect of the differences between the forecast and the observed hurricane characteristics. Here we examine this in terms of hurricane strength and hurricane landfall location.

4.3.1.1. Difference in Hurricane Strength Between Forecast and Observation

In chapter 2 we found that hurricane strength has a statistically significant impact on oil input to refineries. Previously, we got the hurricane strength information from the forecast issued by the National Oceanic and Atmospheric Administration (NOAA) National Hurricane Center (NHC). In this chapter, we also collect data on the actual hurricane strength category upon landfall. The interest is the difference in hurricane strength between the forecast and what actually happened. The strength measure we use involves the mean wind speed by category in the Saffir-Simpson Hurricane Wind Scale (SSHWS) indicator. In the SSHWS the hurricane categories do not reflect constant differences in wind speed interval. This means, the difference of the impact between Category 3 and Category 1 is not the same as that between Category 4 and Category 2, even though both of them have the difference of two levels of hurricane categories. To solve this problem, the differences in mean wind speed is computed between the forecast and the observed categories.

Also, as we did in Chapter 2 we consider different forecast windows - 24-hour, 36-hour, 48-hour, and 72-hour forecasts. Notice that the n-hour forecast data we use are the hurricane strength forecast at the landfall location n hours before it lands in Gulf Coast region. For instance, 48 hours before landfall in Gulf Coast, the 48-hour forecast tells what the hurricane strength at the landfall location will be; while 24 hours later, in other words, 24 hours before landfall in Gulf Coast, the 24-hour forecast updates the hurricane strength at landfall location. Therefore, in this chapter, we use forecast from these forecast windows.

Table 4.1 Saffir-Simpson hurricane wind scale

Category	Wind Speed (miles per hour)	Mean Wind Speed (miles per hour)
Five	≥ 157	–
Four	130–156	143
Three	111–129	120.5
Two	96–110	103
One	74–95	84.5
Tropical storm	39–73	56
Tropical depression	≤ 38	–

4.3.1.2. Difference in Hurricane Landfall Locations Between Forecast and Observation

The hurricane landfall (strike) location is also important in characterizing the results of decision making on oil input. If the forecast says the hurricane will go to the direction of Corpus Christi, Texas, then refineries in New Orleans, Louisiana may not take action. However, the hurricane path is dynamic and can change with forecasts updated up to 4 times every day. In this case, 48-hour forecast of the landfall location can be different from the actual landfall location.

Following Chapter 2, we use four sub-regions (Corpus Christi, Houston-Galveston, Port Arthur-Beaumont, and New Orleans) that have differing capacity shares (11%, 31%, 29%, and 29%) based on the data from the 2018 EIA refinery capacity report (EIA, 2018b). In our analysis the differences between the forecast and actually observed hurricane strike locations will be represented by the difference in the capacity shares between the forecast and the outcome. For instance, in a past hurricane event, if the 48-hour forecast said the hurricane would go to the direction of Houston-Galveston area (31%) and Port Arthur-Beaumont area (29%), which would make the affected share be 60%, but the hurricane eventually struck Corpus Christi area with the actually observed affected share of 11%, then the difference in the affected share would be 49%. Later in this chapter, we will explore, for example, how this 49% affected share difference brought by the inaccurate forecast impacts oil inputs.

4.3.2. The Difference of the Weekly Refiner Net Input of Crude Oil

With the difference of the hurricane characteristics between forecast and the observation, we also need to know what this does to oil input to refineries, so that we can explore their relationship.

Previously, we used the weekly input of crude oil to refineries in the Gulf Coast (PADD3) region that covers the time span from 2001 to 2018, provided by the Energy Information Agency database (EIA, 2019b). After taking out seasonal and trend effects using additive decomposition, we get a stationary series on oil input, which then are related to the hurricane forecast accuracy characteristics. This time, since the explanatory variables are differences of the hurricane characteristics between forecast and the observation, we will use differences in oil input to refineries.

In Chapter 2, we built a model that predicts oil input to refineries (shutdown amount) given hurricane characteristics. Using that model, we predict the amount of the oil input to refineries with the observed hurricane strength and affected shared of capacity (determined by the landfall location). This predicted value can be viewed as the oil input to refineries (shutdown amount) under an accurate forecast, because with an accurate forecast we should get same hurricane characteristics as the observation. Similarly, we get the oil input to refineries under the alternative forecast windows, which could be the same or not with the observation and can be viewed as the original forecast. Our goal here is to take the difference between oil input to refineries under original forecast and that under accurate forecast.

4.4. Method

The main goal of this chapter is to explore whether and how, if yes, inaccurate forecasts will have economic impact on the refinery oil input. The idea is developed from Chapter 1, where we have drawn the conclusion that both hurricane strength and the hurricane landfall location have statistically significant impact on the refineries' oil input. Similarly, to study the (inaccurate) hurricane characteristics forecast on the oil input to refineries, we use the time series decomposition method, removing the effect of trend and seasonality that are imbedded in this data, and only use the remainder of weekly oil input.

Time series decomposition models have different forms – additive form, where the time series data is considered as the sum of the decomposed patterns, and multiplicative form, where the time series data is taken as the product of the decomposed patterns (Prema and Rao, 2015). Additive decomposition model works when the seasonal patterns do not change that much along the time, while multiplicative decomposition model is effective when the variations in the seasonal pattern or around trend are proportional to the level of the time series (Prema and Rao, 2015; Hyndman and Athanasopoulos, 2018). For this reason, we choose additive decomposition model over multiplicative decomposition model. We also check the stationarity of the weekly oil input data using the augmented Dickey-Fuller (ADF) test. That test result shows that this time series data is stationary, indicating that the mean and variance of data are constant over time, so no further adjustment is needed. The additive decomposition model is shown as follows:

$$y_t = T_t + S_t + R_t$$

where T_t is the trend component

S_t is the seasonal component

R_t is the remaining component.

In the decomposition, firstly, T_t, the trend component, is extracted by using moving average of the symmetric windows at time t. Seasonal component S_t, is computed by averaging, for each time unit (week in this case), over all periods, after removing the trend component. Then the remaining component R_t is the portion left after taking out trend and seasonal components from the original data (Hyndman and Athanasopoulos, 2018).

Previously, we regressed the remaining component of oil input on the hurricane characteristics forecast to find their relationship. So, using the model from Chapter 2, we can get predictions of oil input to refineries under two situations. In the first situation, we can get the oil input shutdown decision taken in response to the original forecast (may be inaccurate):

$$\widehat{R}_{inaccurate} = \beta \mathbf{X}_{original\ forecast}$$

Under the second situation, we can get the oil input shutdown decision that would have occurred based on a perfect forecast (where forecasts in strength and capacity affected matches the actual observation):

$$\widehat{R}_{accurate} = \beta \mathbf{X}_{observed}$$

Under our hypothesis, the difference (ΔR) in the oil input decision between the two situations could be explained by the difference in the hurricane forecast:

$$\Delta R = \alpha_1|\Delta x_1| + \alpha_2|\Delta x_1| * sign(\Delta x_1) + \alpha_3|\Delta x_2| + \alpha_4|\Delta x_2| * sign(\Delta x_2) + e$$

where

$$\Delta R = \widehat{R}_{inaccurate} - \widehat{R}_{accurate} \tag{1}$$

$$\Delta \mathbf{X} = \mathbf{X}_{original\ forecast} - \mathbf{X}_{observed} = \begin{bmatrix} \Delta x1 \\ \Delta x2 \end{bmatrix} \tag{2}$$

ΔR is the difference in the oil input remainder components between original forecast and accurate forecast,

Δx_1 is the difference in affected share of capacity (related to hurricane path),

Δx_2 is the difference in hurricane strength,

e is a white noise error term.

Notice that we used the absolute value and the sign value (1 if positive or -1 if negative) of the difference in hurricane characteristics to capture the effect of difference from both sides. In other words, without the absolute value and sign value of the explanatory variables, the model would only examine the cases where the original forecast portends a stronger storm than landfalls, since with the opposite case, the results would show benefits. This is not plausible because it does not make sense to draw conclusion that inaccurate forecast can bring benefits. Adding absolute value and sign value solved this issue.

There are different forecast windows for the original forecast in previous study, thus here we maintain those windows as different scenarios or specifications when calculating the difference in the hurricane characteristics ($\Delta\mathbf{X}$). We add the interaction terms in the model as needed. The results of the model are shown and discussed in the next part.

4.5. Results

Table 4.2 shows regression results of the model. Three columns represent the estimations of the difference in the oil input remainder that arises between the original forecast and the observation in each of the 24-hour, 36-hour, and 48-hour forecasts. Notice that we do not include the 72-hour window because some hurricanes and tropical storm with lower categories do not have such forecasts, so difference is impossible to obtain. The rows represent the explanatory variables or terms – the absolute value of the difference in the affected share of capacity between original forecast and the observation, the product of the absolute value and the sign value of the difference in the affected share of capacity between original forecast and the observation, the absolute value of difference in the wind speed in miles per hour between the original forecast and the observation, as well as the product of the absolute value and the sign value of the difference in wind speed between original forecast and the observation. The numbers in the tables are the estimated coefficients for the corresponding variables, while the numbers in parenthesis are standard errors and the asterisks represent significance level.

We can find that generally both affected share of capacity and hurricane strength are statistically significant and negative for 24-hour and 36-hour forecasts but only affected share of capacity is significant for 48-hour forecast.

The specific effect on the oil input decision difference can be interpreted by the difference in the hurricane characteristics. For example, in the scenario of 24-hour forecast window, we can find that other things being equal, if there is a 10% inaccuracy in the affected capacity forecast, then about 74 thousand barrels of oil input to refineries per day would be falsely reduced. Under a 36-hour and 48-hour forecast window, this 10% inaccuracy in the affected share of capacity would have an added 28 and 36 thousand barrels impact, respectively. From these results, if the refineries management make shutdown decision based on the 24-hour forecast, and the forecast report said the hurricane would go to the direction where both Houston-Galveston and Corpus Christi would be at risk (receive hurricane warnings), but eventually the hurricane struck Corpus Christi, we would estimate that this inaccuracy forecast would lead to 229 thousand barrels of oil input reduction, with other things held constant.

Forecast inaccuracies can also involve hurricane strength. Here as explained in the Data section, we use differences in forecast wind speed in miles per hour. The results show, for example, that if the 24-hour forecast says the landfall hurricane category will be Category 2 but it turned out to be Category 1, then the estimated oil input to refineries would be reduced by 117 thousand barrels of oil input per day. This is calculated using the estimated coefficient times the difference in the mean wind speeds in Category 1 (84.5 mph) versus Category 2 (103 mph), using the 24-hour forecast window estimation.

If we compare the results across the scenarios of forecast window, we can find that model with forecast window of 24-hour has the relatively largest coefficient of determination. Also, the coefficient of determination goes down the as the forecast window becomes longer to 48-hour. One possible explanation is that as the strike time shows the hurricane closer to the Gulf Coast, then forecast reliability increases.

Table 4.2 Regression results

	Dependent variable:		
	diff_y_24	diff_y_36	diff_y_48
	diff in oil input remainder (24h)	diff in oil input remainder (36h)	diff in oil input remainder (48h)
	(1)	(2)	(3)
abs diff in share 24h	-249.489		
	(190.412)		
abs diff in share: sign diff in share 24h	-490.044^{***}		
	(151.286)		
abs diff in wind speed 24h	-2.705		
	(2.032)		
abs diff in wind speed: sign diff in wind speed 24h	-3.693^{*}		
	(1.813)		
abs diff in share 36h		-24.215	
		(188.254)	
abs diff in share: sign diff in share 36h		-252.562^{*}	
		(136.136)	
abs diff in wind speed 36h		-7.232^{***}	
		(2.048)	
abs diff in wind speed: sign diff in wind speed 36h		-8.491^{***}	
		(1.612)	
abs diff in share 48h			33.205
			(189.534)
abs diff in share: sign diff in share 48h			-325.244^{***}
			(111.592)
abs diff in wind speed 48h			-0.532
			(2.659)
abs diff in wind speed: sign diff in wind speed 48h			-2.509
			(2.257)
intercept	-56.930	-104.545	-123.687^{*}
	(56.713)	(63.565)	(68.240)
R^2	0.609	0.693	0.461
Adjusted R^2	0.531	0.631	0.353
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

4.6. Discussion

4.6.1. Economic Loss

Given the results above, we now can estimate the economic loss associated with hurricane forecast inaccuracy. The economic loss of refineries can be estimated by estimating loss in output. As in chapter 2, we use the crack spread procedure with the rate of 3:2:1 (EIA, 2012) to estimate a typical U.S. refinery's output yield based on the input. The 3:2:1 crack spread indicates that a refinery can use three barrels of the crude oil as input to produce two barrels of gasoline and one barrel of distillate fuel. Each barrel equals 42 gallons. Thus, if we get the average prices of the output gasoline and distillate fuel, we can use this relationship to estimate the output loss from inaccurate hurricane forecast. The estimation formula is the following:

$$\text{Estimated output sale loss per day} = \left(\text{Gulf Coast conventional gasoline price} \times \frac{2}{3} \times 42 + \text{Gulf Coast ultra-low sulfur diesel price} \times \frac{1}{3} \times 42\right) \times \text{reduction in oil input in barrels/per day}$$

Here we use a 12-year average price for U.S. Gulf Coast conventional gasoline over the interval August 2010-2021 for gasoline ($2.09/gallon) and a 12-year average price for U.S. Gulf Coast Ultra-Low Sulfur No 2 Diesel for the distillate fuel price ($2.14/gallon). Data used in these calculations are drawn from EIA (2021a; 2021b).

To estimate the output sale loss per day, we use an illustrative example. Assume under the inaccurate hurricane forecast, the 24-hour forecast predicted a Category 2 hurricane while it turned out to be Category 1 (i.e. the mean wind speed of the original forecast was about 18.5 mph greater than the accurate one), also the 24-hour projected hurricane path was for hurricane warnings in the Houston-Galveston and Corpus Christi region while it actually went to Corpus Christi (i.e. the difference in the affected shared capacity was 31%), then the estimated crude oil input being affected (reduced) would be about 346 thousand barrels per day, other things being equal. In this case, the estimated output sale loss for this Gulf Coast region will be approximately $30M per day and $210M for the event week.

Notice that this estimated sale loss solely comes from hurricane forecast inaccuracy. In other words, if the hurricane forecast accuracy improves, for example, to a level that is with accurate hurricane category (i.e. no difference in hurricane strength between the original forecast and the eventual observation) and lower errors in the landfall location (e.g. only 10% difference in the affected share of capacity between original forecast and the eventual observation), then sale loss from hurricane forecast inaccuracy would become 74 thousand barrels per day, which could reduce the output sale loss to $6.5M per day and $45.5M per week, a more than 75% improvement for loss prevention

4.6.2. Operating Profit Loss

Apart from the economic loss, industry commonly pay more attention to the profits to be affected. Thus, we can also value the hurricane forecast accuracy in term of profit loss. Operating profits are calculated by subtracting operating cost (here is refining cost) from the revenue as shown below:

Estimated operating profit loss per day = (Gulf Coast conventional gasoline price $\times \frac{2}{3} \times$ 42

+ Gulf Coast ultra-low sulfur diesel price $\times \frac{1}{3} \times 42$

- Crude oil price/barrel
- Refining cost of gasoline/barrel
- Refining cost of diesel/barrel)

$\times$ reduction in oil input in barrels/per day

Typical refining costs are $0.60 per gallon ($25.20) for gasoline and $0.49 per gallon ($20.58) for diesel (*What Determines Retail Prices for Gasoline and Diesel*, 2016). If we use the same example as the one mentioned above, where assume the hurricane forecast bring about 18.5 mph difference in wind speed as well as 31% difference in the affected share of capacity compared with the observation (or accurate forecast), then the hurricane forecast inaccuracy itself would amount to approximately $33M in profit loss for the event week.

4.6.3. Price Endogeneity

The above analysis and economic loss estimation are based on the very short term before taking into the account of the price endogeneity. In reality, we also need to consider the effect from the price change. Specifically, short supply due to the hurricane forecast inaccuracy could increase the price of the gasoline and diesel, and thus will reduce producer surplus loss (or even increase the producer surplus) to some extent.

However, on the other hand, the consumer surplus will be sure to get negatively affected due to the short supply and the increasing price.

4.7. Conclusions

Many petroleum refineries are located along the U.S. Gulf Coast. This region is vulnerable to hurricanes, and this vulnerability could increase under climate change. When there is a hurricane or tropical storm, refineries in this region typically either shut down or reduce production, with the severity of action based on the hurricane forecast issued by NOAA National Hurricane Center. The forecast, however, could be inaccurate.

To study the economic impact of inaccurate forecasts we examine the relationship between the characteristics of a forecast versus actual characteristics and the difference in oil inputs to refineries. In terms of forecast inaccuracies, we consider the differences between forecast and actual land strike wind speed and location associated affected share of refinery capacity. The model is built under different forecast windows, from 24-hour to 48-hour.

The results show that inaccurate forecasts will lead to more larger oil input reductions along the U.S. Gulf Coast. This effect shows in both inaccurate forecasts of affected share of capacity and hurricane strength within the 24-hour and 36-hour forecasts but only in affected share of capacity in the 48-hour forecast window. Moreover, closer forecast windows (24-hour and 36-hour) display higher goodness of fit (i.e., higher coefficients of determination, R^2) than in the farther out 48-hour forecast window. This is not too surprising because hurricane forecasts keep updating as hurricanes approach the land, more information can provide better forecast results.

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The potential losses in sales and operating profits are also estimated. In a hypothetical case, for example, suppose that the hurricane forecast (inaccurate) is 18.5 mph higher than the actual storm as it makes landfall and that the affected share of capacity is 31% higher than the affected capacity. If the improvement provides accurate forecast in category and exhibits only a 10% error in affected share of capacity, then the improvement in forecast accuracy could result in preventing more than 75% of the value of the sales lost and the operating profit loss. But this loss estimation involves a no change in prices assumption and thus is flawed. With price endogeneity, where lower supply of oil input can in turn increase the price of petroleum products, the producers may not lose as much while the consumers' welfare would be diminished.

There are some limitations of the study. First, the estimation of the impact of the inaccuracy in hurricane forecast on the refineries along the U.S. Gulf Coast is based on the approach used in the chapter 2 study. Thus, the estimation limitations there also carry over to here. Specifically, to explore of impact of the inaccuracy in hurricane forecast, we use two main determinants, the difference in the affected share of the capacity (which is associated with the hurricane landfall locations) and the difference in the hurricane strength in wind speed miles per hour. However other, omitted factors like rainfall may also have an impact. Thus, future study improving the previous study on the economic impact of hurricanes may also contribute to improve the model of this study.

Also, in estimating the economic loss, we only consider the producer's perspective ignoring price changes. Lower supply due to exogenous variables (hurricane forecast inaccuracy here) will move the supply curve to the left and thus result in a higher equilibrium price. Then the loss in the producer surplus will be partially made up by the higher price. The consumers' surplus would definitely decrease due to the higher price. Thus, future work could estimate the loss from consumers' perspective as well.

5. CONCLUSIONS

5.1. Conclusions

In this dissertation, we studied the impact of hurricane characteristics and hurricane forecast accuracy on aspects of oil and gas industry operations and production. The main conclusions by essay follow.

In Chapter 2 (the first essay), we examined the economic impact of forecast hurricane characteristics on Gulf Coast refinery region wide weekly oil input. In doing this we first used time series decomposition to remove any trend and seasonal effect from the oil input data, and then regressed the remaining portion of the oil input on hurricane forecast characteristics including the hurricane forecast category and forecast affected share of capacity of the oil refineries that were within the forecast landfall path using generalized least squares. We included different forecast windows as different specifications, including 24-hour, 36-hour-, 48-hour, and 72-hour forecast.

The results show that generally in each forecast window, the higher the forecast hurricane category or the higher the share of capacity in the forecast path, then the higher the reduction in oil input, other things being equal. To estimate the economic loss from that, we used a standard practice called the 3:2:1 crack spread to estimate the impacts on gasoline and distillate fuel sales losses from the crude oil input reduction. We also estimated changes in the operating cost of the refineries, allowing us to estimate changes operating profits given the change in sales cost. Taking 36-hour forecast of a Category 3 hurricane as an example, we find that the output sale loss could be as high as

$51M per day over the strike week and $35M per day over the following recovery period.

In Chapter 3 (the second essay), we studied the economic impact of hurricane strength and path forecasts on offshore U.S. Gulf Coast oil and gas operations. We explored the relationship between the forecast wind speed and offshore oil and gas production shutdown rate as well as the platforms and rigs evacuation rate using Beta regression due proportional nature of the dependent variables. Similar to the work done in Chapter 2, four forecast windows were considered.

We find that only the forecast that a hurricane will occur is associated with larger oil and gas platform shutdown rates but that forecasts of hurricane strength plays a role in evacuation rate. Namely whether an approaching storm is categorized as a hurricane appears to matter more in the shutdown decision than does the forecast wind speed. But for evacuation rates then wind speed is the important factor. A possible reason could be that oil and gas production shutdown is a standard safety procedure regardless of strength and takes some time, but that platform and rig evacuation depends on whether the storm appears strong enough to merit such action plus can happen more quickly. The essay also presents estimates of economic loss where we find that with a 20 mph increase in the expected forecast wind speed from the threshold of the hurricane Category 1 (74 mph), oil production and gas production would each decrease by about 10% generating an estimated revenue loss of approximately $9.4M per day and operating profit loss of approximately $1.4M per day. Also, the revenue and profit loss are likely to be larger if the hurricane intensity increases under projected climate change.

The first two chapters examined the impact of hurricane forecast characteristics on onshore oil input and offshore oil and gas facility operation. However, forecasts are not perfect with historical performance showing differences between forecasts and actual landfall observations. Thus, in Chapter 4 (the third essay), we estimated the economic impact of hurricane forecast inaccuracies on the Gulf Coast refineries. We used the same basic approach as in Chapter 2 but looked at the effects of the differences between the original forecast and actual observation in wind speed and affected share of capacity using a multiple linear regression model.

Results show that inaccurate forecast will result in larger reductions in oil input. Also, we find that both forecast inaccuracy in predicting the affected region (embodied as affected share of refining capacity) and in the hurricane strength (embodied as category mean wind speed) causes larger reductions in oil input, profits and sales. Also, we assumed a scenario where if the forecast hurricane strength is improved from one category difference to the same as observation, and the forecast share of capacity is improved from difference of 31% to 10%, then the improvement will result in preventing more than 75% of sale loss and profit loss.

5.2. Limitations and Future Research

There are some limitations to this work. First, there may be more potential hurricane attributes factors to consider. In all essays, we only considered hurricane strength (category or wind speed) and/or hurricane landfall location (embodied as affected share of capacity of refineries), whereas other weather factors such as precipitation amount and storm surge are also likely to affect petroleum refining process and offshore oil and gas production. Also political, pandemic and economic events may also influence production. Future research could incorporate these factors perhaps improving estimation of the economic loss.

The second limitation is about the refinery data we used in the Chapter 2 and Chapter 4. We were unable to get the oil input data at the refinery or regional level due to business confidentiality. Thus, in our study, we grouped the refineries along the U.S. Gulf Coast into four subgroups based on their geographic locations, and then used the share of capacity as the weight in each subgroup. This grouping method, on one hand allowed us to proceed without regional level data, but on the other hand still cannot provide as much information as would more disaggregate data. If it is possible to access more disaggregate data for the study in the future research, more insights would be provided.

Moreover, we estimated economic loss and operating profit loss across all essays. We not only provided the loss per day but also estimated the loss for the whole event week plus the recovery period. The following week was used as the recovery period in our study for estimation, but the actual recovery period could be different subject to the specific events. For major and severe hurricane, the recovery period could be up to a few months (Crooks, 2021). Thus, further study could explore inclusion of information on recovery and thus have a better estimation of the economic loss.

Finally, in estimating the output sale loss and the operating profit loss for the energy entities, out method is to use fixed average prices of the crude oil and the associated petroleum products including gasoline and diesel. If we consider price response, then prices would likely increase as the supply curve would shift to the left. This indicates that economic loss from the hurricane forecast or forecast inaccuracy may not be (only) reflected on producers but would also be reflected on consumers. Consumer surplus will be negatively affected due to the price increase. Future study could consider this issue involving price changes and from consumers’ perspective.

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